Pathways through the green transition and beyond: applying networks to industrial strategy, labour markets, and productive knowledge

Joris Bücker

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School of Geography and the Environment
Institute for New Economic Thinking at the Oxford Martin School
Smith School of Enterprise and the Environment
St Edmund Hall
University of Oxford

Abstract

Decarbonising economic activity quickly is one of the greatest societal challenges of our time. In this thesis, I present two papers on the structural change associated with this green transition and one that concerns structural change more broadly. All three papers – on green industrial strategy, labour market frictions during the green transition, and a new measure of product-level productive knowledge – assess structural change through the lens of path dependencies.

Climate change action requires structural economic change, and policymakers increasingly use green industrial strategy to steer that change. Paper 1 introduces a novel dataset of green industrial policies targeting products along the value chains of solar PV, wind energy, and batteries. We show that the fraction of green policies has grown steadily around the world between 2010 and 2022. We introduce three networks of policy relatedness between policy instruments, targeted products, and implementing countries, respectively. These networks are informative of new policy adoptions, indicating that green industrial strategy is path-dependent in multiple ways.

Even with the right policies, structural change takes time, during which a country's labour market needs to adjust. Using an input-output model coupled with an occupational mobility network, Paper 2 shows how a rapid US power sector decarbonisation can lead to labour market frictions for specific occupations and tracks how these might evolve over time. We show that there are three distinct temporal demand phases and, based on these phases, propose a fourfold typology of occupations that nuances the green vs brown occupation debate. Compared to the size and fluctuations of the US labour market, the impact of this transition is modest. However, without proper planning, rapidly growing industries may struggle to find skilled labour during the scale-up phase, and displaced workers might struggle to find jobs during the scale-down phase.

Skills and productive knowledge not only constrain the careers of individual workers but also affect the growth paths of entire countries. This is important not only for the green transition but for structural change in general. Paper 3 introduces a new measure of productive know-how at the product level. Our measure, called product skill intensity, is based on the educational attainment of workers in occupations required to manufacture the product. We discuss product-level insights, including the relationship with the product space, and country-level insights, where we show the association of skill intensity of exports with GDP growth and export diversification between 1995 and 2019.

Together, these papers suggest that local network interactions can affect the trajectory of the green transition and structural change more broadly. The transition's interactions with the economy's network structure can lead to frictions, and path dependencies can lead to inertia. While this suggests that the green transition may not be implemented as smoothly as planned, this thesis can help understand these risks – and addressing them can help maintain or increase the pace of the transition.

Contents

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DPhil papers

1. Interlocking path dependencies in green industrial strategy

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2. Employment dynamics in a rapid decarbonization of the US power sector

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Joris Bücker, R. Maria del Rio-Chanona, Anton Pichler, Matthew C. Ives & J. Doyne Farmer

3. From potatoes to silicon chips: the role of product skill intensity in structural change

Submitted to World Development

Joris Bücker & Penny Mealy

1 Introduction

Structural change is paramount to decarbonisation. The global economy requires a shift to a net-zero energy system while supplying the energy we need at an affordable price (e.g., McCollum et al., 2018; Rogelj et al., 2015; Davis et al., 2018; Pickering et al., 2022; Fankhauser and Jotzo, 2018; Mulugetta et al., 2022; Steffen et al., 2018). To limit warming to 1.5 to 2 degrees and reduce the potential for catastrophic consequences of cumulative greenhouse gas (GHG) emissions, the world needs to reach net-zero GHG emissions between 2045 and 2080 (Allen et al., 2009; Meinshausen et al., 2009; Steffen et al., 2018; IPCC, 2018), requiring immediate and substantial action (IPCC, 2022). This decarbonisation must be incentivised or otherwise guided by policy (e.g., through carbon pricing) (Stiglitz, 2019; Klenert et al., 2018; Blanchard et al., 2023; Carattini et al., 2018) and will change the structure of local economies, including their labour markets (Mayfield et al., 2023; Xie et al., 2023) and competitiveness (Mealy and Teytelboym, 2022; Andres et al., 2023).

More than three-quarters of emissions are due to energy-related processes (IEA, 2023a). Solar PV, wind energy, and batteries, in particular, will change the energy landscape (IEA, 2024b,a), although a diverse range of low-carbon technology mixes is available (Pickering et al., 2022). These renewable technologies are, in aggregate, very different from fossil fuel-based ones, requiring different types of knowledge and skills to make, deploy and manage (Jee and Srivastav, 2024). In addition, adaptation to the realities of climate change – beyond the scope of this thesis but important for the transition – will require new ways of working (Day et al., 2019), infrastructure (Fankhauser et al., 1999), and development paths (Bowen et al., 2012). In all, a possible low-carbon ‘industrial revolution’ is beckoning (Pearson and Foxon, 2012).

Energy is an input to practically all economic activity, and its fluctuations in price and availability have an outsized impact on the total economy (Baqaee and Farhi, 2019). Virtually every economic sector will have to rewire to renewable sources to accommodate decarbonisation. For grid electricity users, the transition is relatively easy. For others, for example industries that require heat or direct combustion, less so. Households need to shift away from fossil fuel-based heating and transportation towards alternatives such as heat pumps and electric vehicles or public transportation. Manufacturing needs to supply the technologies required. The production of wind turbines, solar panels, heat pumps, and batteries for electric vehicles (EVs) all need to scale up drastically (IEA, 2023b). All of this needs to be made, shipped, and installed in a clean manner. Further upstream, mining will shift from fossil fuel extraction towards metals and minerals required for low-carbon technologies, including lithium, cobalt, and rare earth elements, and this needs to be done with limited environmental impact or increased reuse and recycling (Sovacool et al., 2020).

More commitments to climate change action are being made every year, including pledges to achieve net-zero emissions by the middle of the century (Climate Action Tracker, 2023). Economic and technological barriers are also getting smaller, and recent studies suggest that a net-zero energy transition is feasible and even financially beneficial in itself due to the decreasing costs of renewables and storage technologies (Way et al., 2022; Creutzig et al., 2023).

However, despite multilateral agreements and climate change mitigation action, global GHG emissions in 2023 were the highest on record (WMO, 2024). With every increment of warming, the consequences and risks of climate change become increasingly difficult to manage (IPCC, 2023). We may be close to peak energy emissions, but fossil fuel-dependent growth can still seem attractive, in particular when the financial gains are local and climate change damages are global (Mercure et al., 2021). Ultimately, more rapid interventions are needed to limit the larger risks of climate change on the earth system (IEA, 2023c; IPCC, 2023), but a rapid decarbonisation of our economic system is not without its own risks.

This thesis looks at three parts of structural change during the green transition and beyond. In particular, it concerns the implications of path dependencies in structural change. First, I look at the dynamics of green industrial strategies. Following a long period of agnostic market-driven growth, policymakers are (re)learning tools to direct growth (Juhász and Lane, 2024) and to steer their economies towards climate compatible 'green' growth (Fankhauser, 2024; Hallegatte et al., 2024; Rodrik and Stiglitz, 2024). Second, I look at labour market frictions during the green transition and the extent to which the required work of deploying renewable technologies is compatible with some of our extant knowledge and skills based on a fossil fuel-dominated energy system (Bowen et al., 2018; Bergant et al., 2022; Saussay et al., 2022; Curtis et al., 2023). And third, I introduce new measures of product- and country-level productive knowledge. This work is not about the green transition per se, but it could help understand the problems that some countries have with limited learning spillovers to green industries due to their lock-in to fossil fuel-dependent growth (Andres et al., 2023; Fouquet, 2016).

I address these topics using a complexity science lens, as all three papers enclosed have a strong network science component. I will briefly explain how the three papers relate to path dependence in the context of structural change and what their individual connections are to the existing literature.

First, I look at the increasing use of green industrial strategy to steer the economic structure towards net zero and climate compatible growth (Juhász and Lane, 2024; Lewis, 2021). While direct carbon pricing is often seen as the first-best policy to address climate change, political opposition to it is strong, and not enough progress has been made in implementing it around the world (Carattini et al., 2018; Jakob and Overland, 2024). Finding the right policy levers has proved tricky, and an expanded toolbox has emerged of individual climate policies and policy mixes to help accelerate climate action, including green industrial strategy (Blanchard et al., 2023; Mealy et al., 2024; Linsenmeier et al., 2022).

In Paper 1, we introduce a novel dataset of green industrial strategy, which includes policies that affect the domestic manufacturing of products along the value chains of solar PV, wind energy, and batteries. We show that green industrial strategy has grown across the world between 2008 and 2022. We find path dependence in industrial strategy: networks of policy instruments, targeted products, and countries reveal a structure of interlocking path dependencies. This indicates that emerging (green) industrial strategy is – to some extent – predictable.

This paper builds on earlier understandings that policymaking is part of a complex system with many path dependencies (Pierson, 2000). Studies have shown that policies affect politicians, interest groups, and civil society, which will, in turn, affect future policies (Pierson, 1993; Béland, 2010; Edmondson et al., 2019; Kammerer et al., 2021). Policies diffuse across national borders (Fankhauser et al., 2016; Kammerer and Namhata, 2018), build on other policies due to state capacity (Linsenmeier et al., 2022; Meckling et al., 2017), and tend to target industries based on their current competitiveness (Juhász et al., 2022).

Second, structural change takes time, during which a country's labour market needs to adjust. Accelerated action and structural change will impact the local economic fabric. The International Labour Organisation calls ensuring environmental sustainability and providing decent work for fulfilling lives the two defining challenges of the 21st century (ILO, 2018a). Their analysis finds net employment gains of a green energy transition, which is in line with most of the literature. But such gains will depend on the right policy (Poschen, 2017), without which the shock may not be distributed evenly and is likely to perpetuate inequality (Carley and Konisky, 2020; Xie et al., 2023). Regionally, income disparities will be even more pronounced (e.g., Baran et al., 2020). Jobs will become more skills-based, possibly requiring more investments in (re)education to make the transition more socially sustainable (e.g. Acemoglu and Autor (2010); Merriam and Baumgartner (2020)).

Paper 2 shows that, while the absolute labour demand impact of a fast decarbonisation of the US power sector is modest compared to the full US labour market, it can lead to labour market frictions for specific occupations – and these can evolve over time. Workers change jobs all the time, and the natural labour market flux constantly re-allocates workers via labour flows between firms (López et al., 2020), which absorb small shocks in labour demand and supply. But this can fail under stress: path dependencies in workers' skills and career paths place constraints on labour mobility (Cheng and Park, 2020). Substantial labour market mismatches can lead to rising open vacancies and unemployment simultaneously (Del Rio-Chanona et al., 2021). We show this can occur during a rapid decarbonisation of the power sector.

Our work relates to two strands of existing literature on how the labour market might respond to the green transition. The first is concerned with estimating how many workers will lose their jobs and, vice versa, how many new jobs will be created during the transition. Such papers usually remain at aggregated levels of the labour market and often exclude the post-transition phase when the new energy system is in place (e.g., Jacobson et al., 2017; ILO, 2018b; Ram et al., 2022; Mayfield et al., 2023; Černý et al., 2022). We demonstrate that a more disaggregated analysis uncovers a variety of demand trajectories for different occupations. These trajectories are non-linear and change as the system gets closer to a new decarbonised equilibrium.

The second strand of related literature tries to identify the difference in skills or other characteristics between 'green' and 'brown' jobs. They aim to quantify the retraining or relocation potential during the green transition at a much finer level. However, they often disregard the changing dynamics over time and sometimes leave out discussing the size of the shock entirely (e.g., Vona et al., 2018; Bowen et al., 2018; Bergant et al., 2022; Saussay et al., 2022). This literature assumes that green jobs will see a steady demand increase and brown jobs will gradually disappear and try to identify potential career moves out of brown jobs or into green ones. In this paper, we make the case that the dichotomous green vs brown narrative is too limiting and propose a more nuanced fourfold typology based on occupational trajectories. Workers and employers face different frictions when finding work or filling vacancies, respectively, and these frictions can change over time.

Finally, skills and productive knowledge not only constrain the careers of individual workers but also affect the growth paths of entire countries. The green transition is a global transition but may require different pathways for different countries (Mealy and Teytelboym, 2022). Developing countries need to find pathways that lead to a more prosperous yet greener society. Simultaneously, wealthy countries embedded in the fossil fuel supply chain will need to come up with a quick, feasible and equitable diversification plan towards a green economy, which may not be easy (Andres et al., 2023). Earlier research has shown the importance of human capital for development and structural change (Arrow, 1962; Mincer, 1984; Mankiw et al., 1992; Hanushek and Woessmann, 2012; Stiglitz and Greenwald, 2014; Hidalgo, 2023) and green jobs are often more skill-intensive (Bowen et al., 2018; Consoli et al., 2016). However, policymakers have struggled to use such insights directly for policy and economic development (Lall, 2000; Blanchard and Olney, 2017).

Paper 3 continues the analysis of changing skill requirements during structural change, focusing on productive knowledge more generally. It introduces several new measures to characterise the skill intensity of traded goods and explores the implications for countries' growth and development. Our product-level measure, called *product skill intensity*, ranks products by their requirement for skilled workers. It is based on the educational requirements for workers in the industries that produce each product. Product skill intensity gives an intuitive ranking of both aggregated product categories and more detailed products within categories. Averaging over a country's exports, we find that *country skill intensity* is associated with higher GDP per capita and future GDP growth. In this regard, our measure can complement earlier human capital metrics such as 'mean years of schooling'. We also find that countries tend to diversify more into products with a positive *skill distance* from a country's level of education.

This paper is directly related to existing literature on structural change and export upgrading, in particular those exploring methods of product-level diversification, such as the product space (Hidalgo et al., 2007), and product- and country-level *sophistication* (Lall et al., 2006), *complexity* (Hidalgo and Hausmann, 2009) and *fitness* (Tacchella et al., 2012). More recently, the literature has started to recognise its strong links to human capital and learning (Balland et al., 2022; Felipe et al., 2024). Hidalgo (2023) identified 'knowledge' as the key capability driving product-level structural change towards higher economic complexity, due to its non-fungibility and natural explanation of path-dependencies. Relatedly, Schetter et al. (2024) created a network of similarities in occupational requirements as the driving force underlying countries' competitiveness.

The findings in this final paper have implications that go well beyond the green transition. Nonetheless, it may have significant consequences when designing country-specific green industrial strategies to diversify towards a more sustainable economy.

The three papers are distinct in their approach but share a similar thematic and methodological focus, which I discuss in more depth in the next sections. Thematically, they follow a complexity science view of structural change during economic development (Paper 3) and the green transition in particular (Paper 1 and 2). Methodologically, all three papers use networks and the lens of path dependence, for policies (Paper 1), occupations (Paper 2), and products (Paper 3).

Together, these papers suggest that methods from complexity science can help understand the dynamics of the green transition and structural change more broadly. Local network interactions can influence the overall speed of the transition. The interactions between the transition requirements and the network structures can lead to frictions, and channels of path dependence can lead to inertia. The transition will not necessarily be smooth, and this thesis can help us understand how to analyse its bottlenecks and other risks. Addressing these risks can help maintain and increase the pace of the transition.

The rest of this framing document is structured as follows. I will first introduce the thematic focus shared by the three papers. Then, I will discuss the methodological focus with an introduction to network science in economics, and subsequently give a literature review on the specific economic networks in this thesis. This is followed by the three above-mentioned papers. The final section is a discussion of the results, where I highlight three overarching insights that transpire from the different papers and suggest potential areas for further research.

1.1 Introduction to the thematic focus

This thesis looks at structural change for the green transition and beyond. I view this topic through the lens of complexity economics and path dependence. I will first briefly discuss what I mean by a complexity science view of economics and the importance of path dependence in this context. I will then discuss the concept of structural change and its relevance for the green transition.

1.1.1 Complexity economics and path dependence

The global economy has been described as a structure that is ‘orders of magnitude more complex than any other [...] ever built by humankind’ (Beinhocker, 2007). Hayek noted that our economic systems are self-organising complex structures (Hayek, 1991; Axtell, 2016). Other important economists, including Adam Smith, have also been said to view the economy as a complex system (Farmer et al., 2012; Beinhocker, 2007).

In the literature, the definition of a *complex system* has proven hard to pin down (Estrada, 2023; Cairney, 2012). It is often defined as a system that is more – in some qualitative way – than the sum of its parts (Herbert, 1996; Beinhocker, 2007). Its features can include nonlinearity, feedback loops, a large number of interacting parts, hierarchical organisation, self-organization, lack of central control, robustness, spontaneous order, emergence (Ladyman et al., 2013; Meadows, 2008), and critical points and regime shifts (Farmer et al., 2012). Estrada (2023) proposes a minimal definition of a complex system after critically reviewing previous ones as a 'system where there is a bidirectional non-separability between the identities of the parts and the identity of the whole'. Arthur (2013) calls complexity economics a more general framework than neoclassical economics, with 'equilibrium' economics a special case. Arthur et al. (1997) identify six features of the economy as an *evolving* complex system, including dispersed interaction, continual adaptation, and out-of-equilibrium dynamics.

The complex systems perspective diverges from some parts of mainstream economics that try to reduce the complexity of the system by simplifying components, such as using a single representative household or firm, or by only considering equilibrium results. Complexity economics tools can be helpful when heterogeneity and dynamics are important, as they are in many real-world phenomena (Farmer and Foley, 2009). During the 2007-2008 economic crisis, for example, conventional methods failed policymakers around the world because the dynamics of entangled financial institutions were not accounted for (Schweitzer, 2018; Farmer et al., 2012; Mercure et al., 2018). The economics of climate change has had a similar problem (Farmer et al., 2015; Stern et al., 2021).

Dispersed interaction in the economy means that more use of disaggregated data often improves modelling outcomes, for example for workers' skills (Frank et al., 2024), technology cost curves (Lafond et al., 2018), or supply chains (Diem et al., 2022). The interactions between the parts result in emergent properties that evolve the system. In a disequilibrium system, the state of a system is not solved via linear algebra but by a 'map' that projects a state forward from its previous state (Pangallo, 2024). This induces path-dependent behaviour, where small shocks to a system can push it to a different stable state, requiring more effort later on to change course.

In fact, path dependency, the idea that the current state (e.g., occupation, technology) determines – to some extent – the next steps, has been observed in many parts of the economy. It has influenced many different strands of research, from classical work on knowledge spillovers (Marshall, 1890) and agglomeration externalities (Ellison and Glaeser, 1999; Diodato et al., 2018), economic geography (Martin and Sunley, 2006), to evolutionary economics (Nelson and Winter, 2002) and complexity economics (Arthur, 1989, 1994). It has since sparked a discussion on whether path dependence can fit within the mainstream paradigm (Liebowitz and Margolis, 1995) or requires a different way of thinking about economics (David, 2001). Path dependence is sometimes conflated with the broader notion that 'history matters', with Vergne and Durand (2010) distinguishing it from related phenomena, such as institutional persistence, structural inertia, first-mover advantage, and chaos theory. They found the determining conditions of path dependence are the presence of contingencies and self-reinforcements that, under a stochastic process, can lead to lock-in.

The empirical implication of path dependence is that early choices can lock in a region's economic structure or a worker's career options, and changing course can be difficult. The persistence of path dependence should not be underestimated. Running their simulations on US agglomeration externalities to the year 3000 (!), Allen and Donaldson (2020) find a bifurcating pattern for some parameter values: small historical shocks can lead to very different long-term spatial distribution of welfare.

Empirically, this kind of long-term persistence has been shown in numerous examples. For example, Glaeser et al. (2015) link the presence of mineral deposits in 1900 to local firm size and entrepreneurship in the 1960s and beyond. In Bolivia, the Spanish *Mit'a*, a forced labour system used until 1812, still leads to a six percentage point higher prevalence of stunted growth and 25% lower household consumption today (Dell, 2010). Franco et al. (2021) find that families living close to the historical Inca Road in Peru still enjoy higher wages and education attainment and a reduction of child malnutrition. Botticini and Eckstein (2016) give several examples of instances of the path dependence of *occupations* in specific groups of people or places, such as the concentration of industries in a particular region, intergenerational persistence of professions, or group effects such as discrimination or conformism.

Path dependence is a feature of many systems beyond economics as well, such as in biology. It is important to note, however, that path dependence in economics may result in costly readjustments but rarely to a situation that is impossible to get out of (Mokyr, 1991). The stakes are higher in biology, where, for example, a pathway in which one species goes extinct can never reach the path where it still exists.

This thesis gives new insights into the existence and consequences of path dependence in three novel applications related to structural change and the green transition, but it does not advance the theory of path dependence. For the purpose of this thesis, path dependence is linked with the principle of relatedness (Hidalgo et al., 2018), which I will explain more in the next section. The three papers in this thesis work with trajectories of disaggregated economic variables – industrial strategy, workers' career paths, and countries' productive knowledge – that are shaped partly by their past and current situation (Hall, 1993; Frank et al., 2024; Hidalgo et al., 2007). They thus stress that heterogeneity and path dependence are essential for understanding structural change.

1.1.2 Structural change for the green transition

Structural change is the reallocation of production or production factors, such as labour, towards more productive sectors (Timmer et al., 2015; Syrquin, 1988) or towards those that expand a region's capabilities (Neffke et al., 2018a). Technological and structural change happens through learning and innovation. Enhanced productive knowledge is one of the most important drivers of economic development and enhanced wellbeing (Stiglitz and Greenwald, 2014; Arrow, 1962; Rodrik and

Stiglitz, 2024).

Indeed, economic development entails structural change (McMillan and Rodrik, 2011; Brummitt et al., 2020). As countries grow from low-income to middle- and high-income status, the composition of the labour market and economic output moves from agricultural sectors to manufacturing and services (Kuznets, 1955). Countries tend to diversify first and specialise again later in their development arc (Imbs and Wacziarg, 2003). In aggregate, these movements have been well known. But, at the detailed level, the empirical diversity of development pathways and the policy strategies needed to achieve competitiveness is extensive (Lall et al., 2006).

Exploring the dispersed interactions and dynamics of structural change, the *economic complexity* literature – a subset of the complexity economics literature introduced above – has risen to prominence in the past 20 years. The seminal Hidalgo et al. (2007) found that their *product space*, a network of products connected by co-export probabilities, constrains the structural growth paths of countries. Export data is used because it is available at high quality and indicates international competitiveness. Hidalgo et al. (2007) found that countries are more likely to grow comparative advantage in products that use similar capabilities to those they are already competitive in. This idea embeds the path dependence in export patterns by design. A lively research field has grown around this insight, adding to the product space a time dimension (O'Clery et al., 2021; Zaccaria et al., 2014), subnational dynamics (Neffke et al., 2011), enhanced methodology (Tacchella et al., 2023), and much more (Hidalgo et al., 2018).

While initially, Hidalgo et al. (2007) used the language of *capabilities*, including "property rights, regulation, infrastructure, specific labor skills, etc." when explaining product- and country-level differences in complexity levels, in recent years, the focal point has shifted towards human capital. Hidalgo (2023) identified 'knowledge' as the key capability, due to its non-fungibility and natural explanation of path-dependencies, and called economic complexity "a development theory more aligned with work focused on learning rather than capital accumulation". The economic complexity literature has expanded its reach to more explicit measures of knowledge as well, including research and development on technologies using patent data (Petralia et al., 2017; Balland and Rigby, 2017; Antonelli et al., 2022) and specific tasks or skills (Divella et al., 2023; Lo Turco and Maggioni, 2022). For example, Schetter et al. (2024) identify a network of similarities in occupational requirements as the driving force underlying countries' structural change. More research on the link between product complexity and human capital has been called for, especially in light of increased automation (Balland et al., 2022).

Nowadays, climate change and changing economic circumstances require development not by economic growth per se but by growth that is climate compatible (Fankhauser, 2024; Bowen and Hepburn, 2014). This requires *directed* technical change (Acemoglu et al., 2012a) and directed structural change (Rodrik and Stiglitz, 2024). In the product space, this implies that certain parts of the product space that rely on fossil fuel-based technology may become obsolete, and pathways towards green technologies become more important (Andres et al., 2023). The path dependence of this process means that the green transition may require costly adjustments in the short run, but, in the longer run, may lead to a prosperous green growth path (Fankhauser, 2024; Aghion et al., 2019; Stern, 2015).

Recently, *industrial strategy*[1], which directly aims at directing structural change, has become back in vogue (The Economist, 2023; Stiglitz, 2017). It has been around for a long time (Wade, 2012) – from Hirschman's supply chain linkage development strategy in the 1950s (Hirschman, 1958), through East Asia's export and growth success (Lall, 2003; Aiginger and Rodrik, 2020) and a myriad of government institutions that foster public-private R&D in many high-income countries (Wade, 2012). But industrial strategy has become increasingly common since the late 2000s

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[1] In this thesis, I use the term 'industrial strategy' for the type of policies that Altenburg and Rodrik (2017) call *structural transformation policies* or *productive development policies*. These are more conventionally referred to as 'industrial policies', which I use when discussing specific policies or policy adoptions.

(Juhász et al., 2022; Wade, 2012). Countries nowadays pursue industrial strategy for a variety of reasons. Although, traditionally, the goal of industrial strategy has been to direct structural change and increase competitiveness, other goals such as supply chain resilience, energy security, and climate change concerns – *green* industrial strategy – are becoming more prominent (Rodrik, 2014; Evenett et al., 2024).

However, the trajectory of industrial strategy remains poorly understood (Evenett et al., 2024). New policy adoptions do not occur in isolation; they influence institutional and political capacity as well as other stakeholders, creating complex feedback loops that drive further policymaking (Pierson, 1993; Béland, 2010; Hall, 1993; Evenett et al., 2024; Juhász and Lane, 2024; Reichardt et al., 2016; Hoppmann et al., 2014; Eskander et al., 2024; Rodrik, 2004). These processes result in path dependencies (Hall, 1993; Pierson, 2000), impacting the diffusion of policy innovations both within and across countries (Berry and Berry, 1990; Fankhauser et al., 2016; Mealy et al., 2024).

Due to the nature of climate change, the case for green industrial strategy is often seen as stronger than industrial strategy more generally (Hallegatte et al., 2013; Harrison et al., 2017; Juhász and Lane, 2024), as it tackles environmental externalities as well as knowledge externalities Rodrik (2014). A third, more practical benefit is that green industrial strategy can help overcome political constraints and be a precursor of more effective environmental policies such as carbon pricing (Linsenmeier et al., 2023; Meckling et al., 2017; Linsenmeier et al., 2022). This has prompted some researchers to suggest that the optimal usage of green industrial strategy is as part of a portfolio of climate change policies (Juhász and Lane, 2024; Blanchard et al., 2023; Jakob and Overland, 2024).

Nonetheless, green industrial strategy can lead to inefficiencies and lock-in effects of their own (Lewis, 2021; Meckling et al., 2017), trade disputes and shrinking international trade (Felbermayr et al., 2017; Barattieri et al., 2024), and misaligned incentives in combination with other policies (Fankhauser et al., 2010), which can all slow green technology diffusion and international cooperation, leading to a more costly transition (Meckling, 2021). Hidalgo (2023) breaks his policy advice down in the “what, when, where, and who” of diversification towards more complex products but explicitly stays away from the crucial ‘how’ question to avoid unsubstantiated arguments. That is understandable, as industrial strategy has been looked at mostly unfavourably in the economic literature (Bora et al., 2000; Lane, 2020). However, there are many instances where industrial strategy was successful in changing an economy’s structure towards a more prosperous trajectory (Lane, 2020), and a growing number of researchers express that industrial strategy can help foster innovation (Rodrik, 2004; Aghion et al., 2015), overcome growth barriers (Lebdioui, 2022), or promote exports (Rotunno and Ruta, 2024).

When considering the industrial strategy implications of the economic complexity literature, doubling down on diversification options that the product space suggests towards incrementally more complex products may be tempting. The implication is that other diversification strategies may be more difficult. However, researchers have cautioned against this (Hidalgo, 2023; Li and Neffke, 2024). Li and Neffke (2024) instead propose using the product space and related approaches to do *anomaly detection* on one’s economic structure. Certain industries may be much smaller than these statistical tools suggest, allowing policymakers to investigate and address what is holding their economy back. Hidalgo (2023) stresses the crucial distinction between the descriptive nature of the product space versus the normative ideas that policymakers might have. Policymakers should first identify the direction that is favourable to them and then produce a policy that is mindful of potential product space inertia on that pathway.

When the course of structural change has been set towards a desirable future, difficulties can arise in the short run. Pivoting away from fossil fuel-based technologies can lead to stranded assets (Caldecott, 2017), technologies (Jee and Srivastav, 2024), and skills (Vakulchuk and Overland, 2024). Not all fossil fuel technologies and skills will become stranded: offshore wind leverages offshore technologies; turbine-based technologies, such as hydropower and wind, can track some of its foundational technologies to the oil & gas knowledge; that is even more the case for drilling-based renewables, such as geothermal energy (Jee and Srivastav, 2024). Anecdotally, Texas has become a hub for geothermal energy because of its workforce skilled in geology, earth sciences, and drilling, including fracking (Foxhall, 2024; Cuthbertson, 2023). One petroleum engineer turned renewable energy planner told the New York Times: "The basics are the same [...]. [W]e install foundations, we install turbines, we build roads, we lay cables." (Krauss, 2023). Training programmes can help. According to Baruah (2019), 25% of those enrolled in the Wind Turbine Technician Program at Lethbridge College in Alberta (Canada) were previously workers from fossil fuel industries.

But without guiding policy, the green transition shock may not be distributed evenly and is likely to perpetuate inequality (Carley and Konisky, 2020; Poschen, 2017). Past experiences of long-term depressions from shrinking industries and mine closures in North England, the US Appalachians, and the German Ruhr areas underscore the importance of managing such structural change and finding ways to alleviate the negative impacts of stranded labour on displaced workers and communities (Oei et al., 2020; Gore and Hollywood, 2009; Olson-Hazboun, 2018; Beatty et al., 2007; Carley and Konisky, 2020). This can impact different kinds of workers differently, depending on their options outside their industry, occupation or region (Berryman et al., 2023; Neffke et al., 2018b, 2024).

The studies in this thesis are embedded in these ideas. Paper 1 is concerned with green industrial strategy and discusses how countries have tried to influence their position in the green energy supply chain. Paper 2 looks at the potential implications of directed structural change by identifying labour market frictions during a rapid decarbonisation of the US power sector. Finally, paper 3 looks at the interplay between economic complexity ideas of structural change and skills and learning through the skill intensity of exports.

1.2 Introduction to the methodological focus

A natural and powerful way to study structural change and path dependence in complex systems is via network science. The economy can be seen as a coupled system of evolving networks (Farmer et al., 2012). Economic networks lay bare the structure of relationships between economic entities. Some of these are physical, such as networks of roads, shipping lanes or electricity connections. Other networks, for example those that carry innovations, interpersonal relationships, or 'information' in general, are less visible. However, their impact on the economy is profound, and Jackson et al. (2021) call the language of *externalities* a unifying framework for these kind of economic networks.[2] Networks also nicely fit Pangallo (2024)'s concept of disequilibrium, where the state of a system is not solved via linear algebra but by a 'map' that projects a state forward from its previous state.

Networks in economics is thus a very broad topic. It has been around for hundreds of years and still remains a vast research area today. I will not attempt to give an overview here, but I point the interested reader to more complete reviews on the topic, such as Jackson (2008); Goyal (2023); Bramoullé et al. (2016); Jackson et al. (2021).

In the remainder of this section, I will give a brief introduction to concepts and metrics in network science that I use throughout the thesis. Section 4 will then provide a literature context for the networks used in this thesis. All papers in this thesis use additional methodology other than network science, which will be discussed in the papers themselves.

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[2] The very wide applicability of networks in economics prompted Doyne Farmer to title his 2022 presentation on economic networks at the Oxford Summer School on Economic Networks "Networks all the way down".

1.2.1 What is a network?

A network is a graph $G = (V, E)$ that consists of a set of nodes $V = (1 \ldots, N)$ and a set $E \in V \times V$ of $M = |E|$ edges.[3] Most networks discussed in this thesis are weighted networks, both directed and undirected. In a *weighted* network, the edges have a certain weight that governs how strong the connection is. In a *directed* network, an edge has a direction from one node to another. In that case, an edge from node i to j is different than one from node j to i. In an *undirected* network, the edge is *between* two nodes, without direction.

A useful mathematical representation of a network is its adjacency matrix A, where element a_{ij} is the edge weight between nodes i and j. $a_{ij} = 0$ means no such edge exists. In weighted networks, a_{ij} can be any non-negative number; in unweighted, it is restricted to 0 or 1. The adjacency matrix of an undirected network is symmetric.

The node and edge choice is not trivial. In labour market networks, for example, nodes can be firms, occupations (Del Rio-Chanona et al., 2021), cities (Frank et al., 2024), or industries (Neffke et al., 2017) that workers move between, or combinations of those (Jara-Figueroa et al., 2018; Berryman et al., 2023). Edges and edge weights between occupations in a labour market network can represent historically observed labour flows (Del Rio-Chanona et al., 2021), skill or task overlap (Mealy et al., 2018; Frank et al., 2024), career move possibilities (Bowen et al., 2018), or co-occurrence in industries (Hartmann et al., 2019) or cities (Muneepeerakul et al., 2013).

1.2.2 Glossary of network science tools and concepts in this thesis

I will briefly describe the main network science concepts and metrics that I use in this thesis. I will start with the principle of relatedness, bipartite networks, and their one-mode projections, which are important background concepts for Papers 1 and 3. I will then briefly list the methods that I use in this thesis to analyse

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[3] When discussing networks, nodes are sometimes also called *vertices*, and edges *links*.

one-mode networks.

Principle of relatedness The *principle of relatedness* says that the growth or appearance of an economic activity is related to the presence of related activities in the same location (Hidalgo et al., 2018; Li and Neffke, 2024). This principle tells, for example, that a country will diversify its export basket into products that are 'related' to products it is already competitive in (Hidalgo et al., 2007), or that industries agglomerate with other industries requiring similar capabilities (Ellison et al., 2010), and more (Wixe and Andersson, 2017; Hidalgo et al., 2018). Recently, it has been shown that this principle also holds for environmental policy (Mealy et al., 2024).

The principle of relatedness is often analysed using a *one-mode projection* of a bipartite network of locations and economic activities. A bipartite network has two distinct sets of nodes, also called 'modes', such as industries and occupations, countries and exported products, or, in ecology, pollinators and flowers. In a bipartite network, edges can exist between the modes but not within. So, in a bipartite industry-occupation employment network, 'healthcare' may be connected to 'nurses' because the healthcare sector employs a lot of nurses. In fact, every network can be rewritten as a bipartite network (Guillaume and Latapy, 2004). The occupational mobility network in Paper 2, for example, can be reimagined as a bipartite network of individual workers' careers and occupations, projected on the occupation mode.

Transforming the bipartite network into *a one-mode projection* is often done to help further analysis (Zhou et al., 2007; Giulio et al., 2022). For example, the industry-occupation employment network can be projected on an occupation network if we are interested in the relations between different occupations directly. In this one-mode projection, all nodes are occupations and edges are defined by shared industry employers. For example, an edge may exist between 'nurses' and 'surgeons' because they are both employed in the healthcare sector.

Bipartite networks projection example I will illustrate the usefulness of the principle of relatedness concept using Hidalgo et al. (2007)'s product space, whose methodology I use in Papers 1 and 3. In a hypothetical mono-partite network G of country-level structural change, nodes represent distinct export baskets of competitive products. Nodes are linked if there is a natural transition between the export baskets. Through their development history, countries 'hop' between the nodes. Not all nodes can be reached from any other with the same ease. The network is thus restricted by how countries can move between nodes. This can give insight into the development pathways of countries and inform policymakers on possible diversification options they can pursue or barriers they may face.

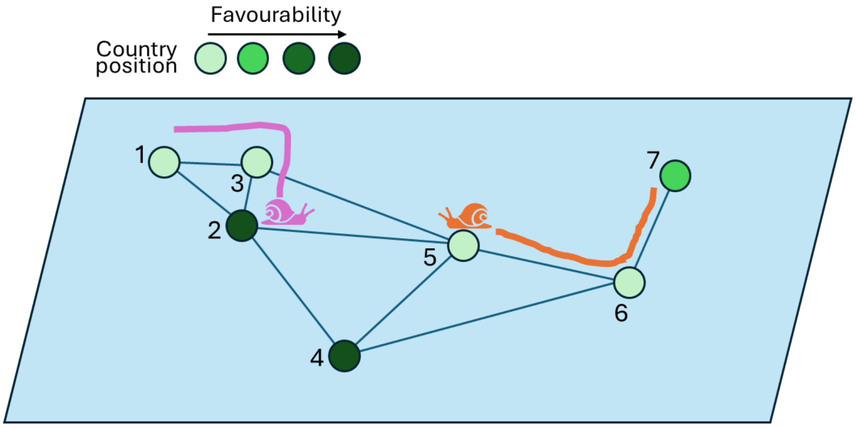

Figure 1: **Pathways on a mono-partite network.** Two snails are depicted traversing the network, leaving a trail so we can observe their paths.

Such a network is shown in Fig. 1: two snails are moving on a network. Because they are snails, we can see the trail they left behind. The pink snail went from node 1 to 3 and 2. The orange snail went from 7 to 6 to 5. Nodes 2 and 4 are the most favourable. We can see that the orange snail had to move from a medium-favourable node (node 7) to a low-favourable node (6 and 5) to be within reach of node 4, choosing the prospect of long-term prosperity over short-term gains.

This stylised example works intuitively, but, depending on the exact specification, this type of network can be intractable and uninsightful. It can work very well for a network of occupations that are connected by their skill-relatedness, as I show in

Paper 2. But it is much harder for a network tracking structural change in countries' exports. If distinct export baskets are defined with sufficient detail, the number of different economic structures – nodes in the network – is vast. With 25 products, if each node represents a unique basket of products, this network would contain $2^{25} - 1 > 30$ million nodes.[4] This network is huge, and country pathways almost surely never cross one another! There are very few observations available for countries. Indeed, one of the main impediments to our understanding of development and economic growth is the limited number of countries on earth compared with potential pathways and mechanisms to influence growth (Durlauf et al., 2005). (Compare this to a labour market network, where millions of workers change occupation annually in the US alone (Vom Lehn et al., 2022).)

Hidalgo et al. (2007) approach this by realising that the dimensionality can be reduced using a bipartite network of countries' economic structure between the countries and products they export competitively. Fig. 2 shows a simple graphical representation of how this works. The bipartite network H comprises both country and product nodes (see Fig. 2a). Edges are drawn between a country and a product if that country competitively exports the product. No further edges are going from country to country or product to product; that is, we do not require knowledge of feasible transition paths a priori but infer them using the cross-sectional variation in country export baskets. We can then create a one-mode network H^p, which is the product-mode projection of H. In H^p, all nodes are products, and edges between two products exist if the same countries export both of them competitively. This one-mode projection is shown in Fig. 2c. Fig. 2b shows how H and H^p relate to one another. This is a stylised representation of a one-mode projection; many ways to specify the one-mode projections for the principle of relatedness have been proposed. See Li and Neffke (2024) for an overview.

Network H^p is tractable even if the number of products exceeds the number of

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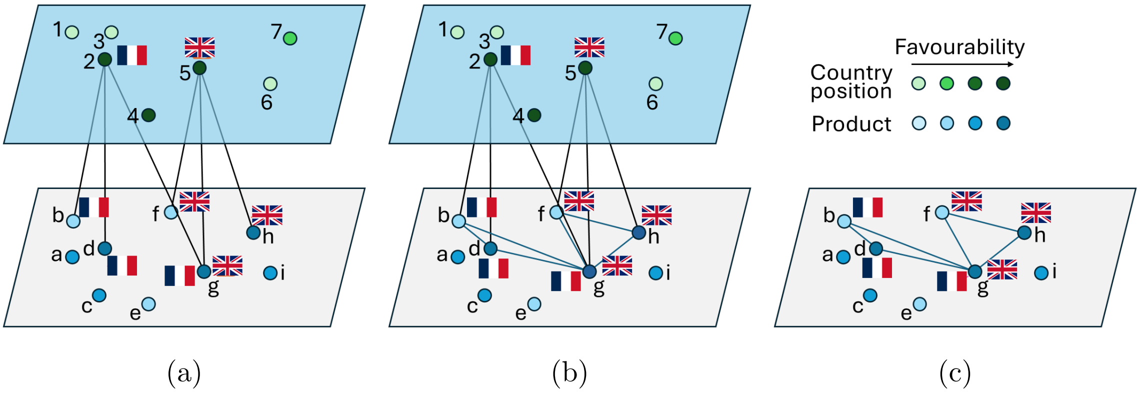
[4] The product space in Hidalgo et al. (2007) contains 775 products.



(a) (b) (c)

Figure 2: **Bipartite network projection example of countries (top) and products (bottom).** Selected edges of example countries are shown. In (a) the bipartite network with two example countries; in (b) the bipartite network with the one-mode projection towards the product mode; in (c) the one-mode projection creates a network of products.

countries. The interpretation, however, is less straightforward than in Fig. 1. In the bipartite projection, countries do not inhabit single nodes that represent their entire economic structure but a group of product nodes: in the lower network of Fig. 2, the countries are mapped on all their competitive products. This is also called an *overlay map* (Rafols et al., 2010). I use this technique in Paper 1 when showing which (type of) countries use what policy instruments on the industrial strategy instrument network.

One-mode projections will not be appropriate for all applications, as some information of the original data is lost, especially when the bipartite network degree distribution is heavy tailed (Vasques Filho and O'Neale, 2018). For example, the product network can only show bilateral product relationships (in Fig. 2c, product b can be reached from products d and g, but the network cannot distinguish between the case where d and g both need to be present or where either one is enough). Some of this information is in the other *country-level* one-mode projection. If both projections of a bipartite network are used, the information loss is actually very small (Everett and Borgatti, 2013). In Paper 1, I present all three projections (policy instruments, targeted products, countries) of the green industrial strategy space. In Paper 3, I follow Hidalgo et al. (2007) and use only the product-level projection.

Assortativity The assortativity of a network indicates how often nodes that are similar on some metric are connected in the network (Newman, 2003). I use this in Paper 2 to identify whether occupations connected in the occupational mobility network are also affected by the green transition in a similar way. In Paper 3, I use assortativity to confirm that products in the product space are often connected to other products with similar levels of skill intensity.

In its simplest form, assortativity is the Pearson correlation between the node's metric of interest and its neighbours' value (Newman, 2003). I follow Newman (2003)'s definition of the assortativity coefficient and other extended versions for weighted and directed networks.

Community detection A related concept is community detection, which is the process of grouping nodes in communities that are connected mainly to other nodes within the same community. I use the Louvain (Blondel et al., 2008) community detection algorithm in Paper 1 to identify the different communities of the green industrial strategy instruments. This algorithm works by iteratively grouping nodes based on their modularity score. It is one of the most widely used community detection methods and applicable to many types of networks, but other algorithms exist too. For example, for flow networks, such as the occupational mobility network, community detection methods based on random walks are often used, such as Infomap (Rosvall and Bergstrom, 2008).

Diffusion, network spreading, and the adjacent possible The *adjacent possible* is a term coined by Stuart Kauffman to denote the set of possibilities that is available for an agent during its evolution by combining items it already has available (Kauffman, 2014). This notion is helpful for this thesis as structural change means moving towards the adjacent possible of the economy in question. A relatedness network provides a straightforward way to incorporate the adjacent possible, as different node combinations can lead to others via the network edges. Indeed, the product space has this exact interpretation: countries build on existing export capabilities to develop new export competitiveness (Hidalgo et al., 2007).

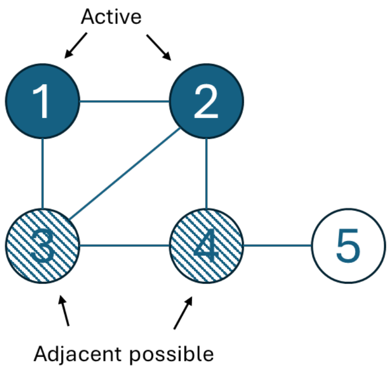


Figure 3: **Adjacent possible.** If the solid blue nodes 1 and 2 are active, then nodes 3 and 4 are the adjacent possible.

Fig. 3 shows a network with five nodes. The nodes are items or technologies that can be discovered, and the edges are ways of discovering new items. Note that we assume here that the outside observer knows the full technology space. The solid blue items (nodes 1 and 2) have already been discovered – they are *active*. The active set is connected to nodes 3 and 4, which are 'discoverable' but not active. This is the set we call here the adjacent possible. Node 5 is not discoverable yet, because it has no direct link to the active nodes, so it is not part of the adjacent possible.

The principle of relatedness entails that the activity is more likely to diffuse or spread to the adjacent possible nodes than to other nodes. On one-mode projections of bipartite networks, multiple nodes can be active, and the extent of being adjacent to the current set of items can be quantified in different ways. In Paper 3, I follow Hidalgo et al. (2007)'s definition of *density* for the product space. Density is defined for items that are not yet active: it is the fraction of neighbouring items that are already active, weighted by edge weight. In Paper 1, I use a similar calculation to measure policy *alignment*. Applied to Fig. 3, node 3 has a density/alignment value of 2/3, node 4 of 1/3, and node 5 of 0. I use alignment to show that new policies are often introduced on nearby products, using nearby instruments, and following nearby countries in the industrial strategy networks. Using the product space, Hidalgo et al. (2007) show that countries more often diversify into products with higher levels of density, which I use in Paper 3. In Paper 3, I also introduce *skill distance* and *skill absolute distance*, which are measures of relatedness between a product and a country based on their skill intensity and mean years of schooling, respectively. We show that countries tend to diversify into products with a positive skill distance and negative skill absolute distance. This indicates that countries tend to diversify towards products that are moderately higher in skill intensity compared to their education level.

Local neighbourhood and outside options Related to the adjacent possible is the concept of neighbourhood in Paper 2. In the occupational mobility network, the 'neighbouring' nodes of occupation a are all occupations that are potential next career possibilities for workers in occupation a. They form the neighbourhood of a that forms its set of outside options for workers in a, the adjacent possible of their career path.

Up- and downstreamness In goods flow networks, downstream industries or products are closest to the final consumer, and produce final goods Upstream industries are involved in exploring, extracting, and processing raw materials. This is related to trophic levels in food webs in ecosystem research (McNerney et al., 2021). In Paper 1, we distinguish between upstream products (raw materials and processed materials) and downstream products (sub-components and end products). In Paper 2, the input-output module of the methodology takes employment changes in upstream industries into account if demand changes from their downstream customers.

Network visualisations We often wish to include a graphical representation of the networks in our work. Network visualisations can be very insightful and aid understanding but can also be misleading, because there are usually many ways one can visualise the same network. Here, I highlight two challenges: dimensionality and density. First, networks are high-dimensional objects. If all nodes are placed at a distance from one another informed by their edge weight – strongly connected nodes are placed closer – it quickly becomes impossible to do in a two-dimensional or three-dimensional space.

There are many ways to force the network into a two-dimensional figure. The standard approach in much of the literature is to use force-directed algorithms. These are known for their general applicability, aesthetically pleasing results (Gajer et al., 2004), and conceptually simple interpretation (Bannister et al., 2012). I mainly use ForceAtlas 2 as implemented in Gephi (Jacomy et al., 2014). Force-directed algorithms can, however, get stuck in one of many local optima. If different local minima lead to very different visual appearances, this can lead to misleading results.

A second challenge arises when networks have high density, i.e., many edges, and end up looking like a 'hairball'. This can be prevented by backboning the network, which is a process of retaining only the important edges (Gomes Ferreira et al., 2022). Due to their high density, the network figures in all three papers are backbone versions. It is important to note, however, that I follow this backbone procedure only for visualisation purposes, and, unless expressly stated, all other quantitative results are calculated using the full network.

In Paper 2, I only include the edges to the top five related occupations in the visualisation. This network is still dense but clearer than the full network. In both Papers 1 and 3, I use a different backbone heuristic, following Hidalgo et al. (2007), which includes the maximum spanning tree (MST) plus all edges above a certain threshold. The MST of a network is the subset of edges that keeps all nodes connected but without loops, i.e., as a 'tree' network, while maximising the sum of edge weights. This ensures that no nodes fall outside the backbone network. Setting the threshold above which all edges will be added to the MST can be arbitrary. In Paper 3, I pick the threshold that maximises assortativity, although I show that the results are robust to the threshold. In Paper 1, I use a different threshold for each of the three one-mode projections so that they give insightful networks.

I chose to use the backbone approaches laid out above for their simplicity, transparency, and widespread use. Still, other more involved backbone methods exist, often leveraging null models to find spurious edges (e.g., Coscia and Neffke, 2017; Pugliese et al., 2019; Gomes Ferreira et al., 2022). Backboning can also lead to unexpected behaviour in combination with bipartite network projections (Coscia and Rossi, 2019).

1.3 Literature background to networks used in this thesis

I will briefly discuss the networks that I use in this thesis. In order of appearance, these are (industrial) policy networks, supply chain networks, labour market networks, and networks of structural change. For each, I will give a brief literature background, including any links between them as well as to the green transition. Fig. 4 shows all networks in one graphic: the economic policy researcher in the centre has an occupation that is part of a labour market network (right side). His presentation shows the interconnectedness of products or industries in the supply chain or development network, such as the product space (left side). He then explains how various industrial strategy options are interconnected in the speech balloon on top.

1.3.1 Policy networks

In Paper 1, we create three different relatedness networks of industrial strategy instruments, products targeted by industrial strategy, and countries implementing industrial strategy. This paper is the first to create networks of industrial strategy, but other policy-related network studies do exist.

As mentioned before, the idea that policymaking, in general, is a complex,

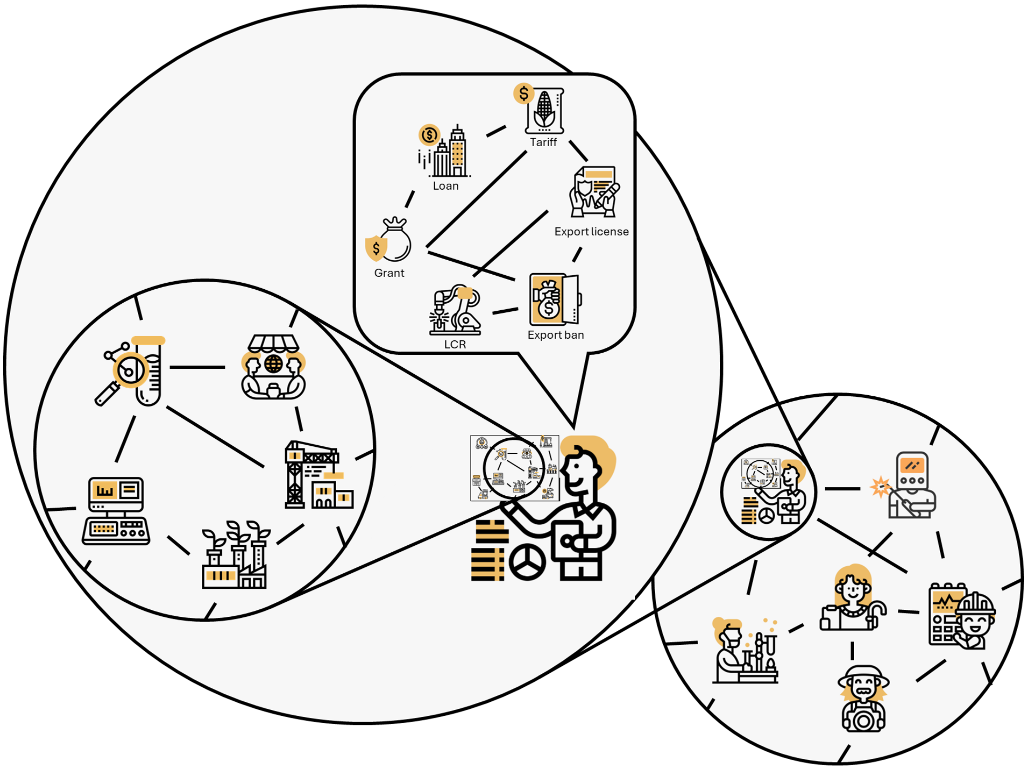


Figure 4: **Networks in this thesis.** Icons from Eucalyp (2019).

evolving, path-dependent process has existed in the literature for a long time (Pierson, 2000). Policy diffusion is the process of countries learning from each others' approaches or otherwise adopting policies that neighbouring or 'related' countries have implemented (Thisted and Thisted, 2020; Fankhauser et al., 2016). Policy diffusion happens between countries along geographic, political, and language borders (Grossback et al., 2004; Mistur et al., 2023). Mistur et al. (2023) liken policy diffusion in the context of battling COVID-19 to the spread of the virus itself.

This process naturally lends itself to network science approaches. For example, Linsenmeier et al. (2023) create a network of countries that are connected if they share specific characteristics. They find that this network can help explain how carbon pricing policies diffuse and how this diffusion changes the policy's emission reduction potential. Kammerer and Namhata (2018) find that a network of country cooperation can also explain international policy diffusion between those countries. A more formal network science approach to US state-level policy diffusion is given by Billard et al. (2020).

At a lower level of government, Lee and Van de Meene (2012) build a network of cities by asking city-level policymakers which other cities they have learned their environmental policies from. Their network suggests that cities with advisory committees on environmental policies learn more often from other cities, and cities with a better environmental policy track record are more often learned from. They also find that geographical and language similarity is important, especially for European and US cities.

Policies not only diffuse across geographical borders but also across policy instruments (Meckling et al., 2017; Linsenmeier et al., 2022; Fankhauser et al., 2016). Mealy et al. (2024) create a network of environmental policies and use the language of institutional capacity to explain path dependencies in policy instrument choice.

Another strand of policy research with a strong network science component examines trade networks and other international treaties. For example, Carattini et al. (2023) build a country network projection from a bipartite country–environmental treaty network. They use various network science techniques to describe how the network of countries connected by treaties has developed over time.

Several further studies use network science to investigate the relationships between policy actors, such as politicians, government officials, or non-state stakeholders (Kammerer et al., 2021; Leifeld and Schneider, 2012; Ingold, 2011). Their network nodes are policy actors, and edges indicate collaboration or the extent to which they trust each other. These social networks can illuminate the complex policymaking processes in different country contexts (Kammerer et al., 2021; Yun et al., 2014).

1.3.2 Networks of supply chains and good flows

Paper 1 defines *green* products as those in the supply chain of solar, wind, and battery technology. Paper 2 uses an input-output network of industry flows to find the upstream effects of the green energy transition. While we do not emphasise their network properties in these papers, supply chains and good flows can be interpreted as networks in which production facilities or industries are nodes, and products flow from upstream industries to downstream industries and then to consumers (Antràs et al., 2012) – and money flows the other way.

Goods flow networks have been part of the economics literature since at least the 18th century, such as Quesnay's 1758 visualisation of a network of economic relationships and flows of goods. Quesnay's *Tableau économique* can be interpreted as a simple input-output network as introduced by Wassily Leontief (Phillips, 1955; Leontief, 1986). Input-output networks are used in Paper 2 and form the basis of many macroeconomic models today. They remain an active field in their own right, too. For example, recent work has stressed the non-linear impact of supply chain shocks in industries (Baqaee and Farhi, 2019; Acemoglu et al., 2012b), the dynamics of more detailed firm-level networks (Inoue and Todo, 2019), the importance of data on global supply chain networks (Pichler et al., 2023), and the interconnectedness between supply chain networks and infrastructure networks (Colon et al., 2021). And a relevant connection to Paper 1 is made by Liu (2019), who show that the impact of industrial strategy on welfare is strongly influenced by the position in the value chain network of the targeted industry.

Similar to our approach in Paper 2, some studies have linked input-output networks to the labour market. Labour is sometimes included in an extended input-output table directly, such as in Miller and Blair (2009)'s closed model with respect to households. Other examples include Garrett-Peltier (2017); Kamidelivand et al. (2018); Markandya et al. (2016); López et al. (2020).

Adding more labour market dynamics, Pichler et al. (2020) exogenously shock labour supply based on how much work can be performed from self-isolation during the COVID-19 pandemic and model their impact through the economy's value chain. Overcapacity leads to workers being laid off, and, when demand picks up, workers are hired. A related example is the model of Diodato and Weterings (2015), in which workers can move to a less-impacted industry or region when a regional economic shock hits the supply chain. Finally, Lloret-Climent et al. (2020) propose a theoretical complex network framework encompassing input-output and labour market relations. Without explicitly mentioning industries, occupations, or I-O input, one can recognise them in the different competition and supply/demand links. Their framework also includes occupational mobility, as they contrast surgeons as relatively *invariant* (i.e. all competing for the same type of job) to supermarket stockers, who perform tasks that are also in demand in many other sectors.

1.3.3 Labour market networks

Network science has featured prominently in labour market studies. Here, I will discuss labour flow networks, skill networks, and other network-related labour market studies.

Labour market networks are often used to identify labour frictions that go beyond the standard labour economics framework of search and matching frictions. In the canonical Mortenson-Pissarides setup, a matching function based on the number of vacancies and unemployed workers governs how many workers and employers 'meet' per iteration (Mortensen and Pissarides, 1994). Subsequently, they bargain over wages to accept or decline the job on offer. This process takes time, causes fluctuations and frictions, and can explain the shape of the Beveridge curve (Elsby et al., 2015).

However, frictions in this model cannot explain the magnitude of empirically observed business-cycle fluctuations, which are much larger (Shimer, 2005). Occupational mobility frictions have been proposed to fill that gap. An extension of the search-and-matching framework model that includes occupational transition frictions leads to labour reallocation an order of magnitude slower than the canonical framework would suggest, as shown by Bocquet (2022) using French data. In a different setup, Guerrero and López (2015) come to a similar conclusion using Finnish data.

Labour flow networks Many labour market networks are based on job-to-job transition data (e.g. Guerrero and Axtell (2013); López et al. (2020)). The merits of measuring job transitions between occupations were already seen in the 1950s and 1980s (Shaw, 1987) – because researchers were worried about the effects of automation (!) – but more access to microdata and better analytical tools made the field grow much faster from 2010 onward.

In labour flow networks, the *edges* are informed by empirically observed job transitions, for example from survey data that tracks people over time (Bocquet, 2022) or from self-reported CV repositories (Frank et al., 2024).

The *nodes* are usually industries or occupations. O'Clery and Kinsella (2022) use worker flows between industries to find *skill basins*, clusters of industries that rely on similar workers, using community detection algorithms. Landman and O'Clery (2020) find that legislation aimed at reducing the gender wage gap changed the inter-industry flows in South Africa. Male-dominated industries, in particular, started hiring new workers from a more diverse set of industries. Networks with industry nodes have also been used to understand regional and firm-level diversification (Neffke and Henning, 2013; Neffke et al., 2017).

On the other hand, networks with occupation nodes have been used to quantify skill frictions (Bocquet, 2022), to understand how occupational mobility relates to skill similarity (Mealy et al., 2018), and to investigate the possible second-order impact of automation on workers' future job prospects (Del Rio-Chanona et al., 2021).

Nodes can also represent combinations of industries and occupations, as is the case in Schmutte (2014). In Berryman et al. (2023), each node is an occupation-region pair in Brazil. Similarly, Park et al. (2019) use a hierarchical network approach to highlight the salience of inter-industry and inter-location mobility.

Some studies use labour flow networks to understand the differences between green and brown jobs. For example, Curtis et al. (2023) leverage CV data to extract information on workers in 'green' jobs in renewable energy and 'brown' jobs in high-polluting and fossil fuel-related industries. They find that brown job workers hardly ever move into green jobs, although the rate is growing. They also explain that a move via a third occupation – neither brown nor green – is more likely than a direct green–brown transition.

Skill networks Edges in occupation networks can also be informed by the occupations' *skill relatedness*. Different occupations require different skills, which can lead to labour market frictions (Autor et al., 2003). Detailed repositories of occupational information, such as the US's O*NET or the EU's ESCO, provide lists per occupation of skills required and tasks performed. Mealy et al. (2018) connect occupations based on the overlap of job activities, weighted by the scarcity of activity. Moro et al. (2021) construct a network using 232 O*NET variables consisting of abilities, interests, knowledge, skills, work activities, work contexts, education, training, and experience associated with each occupation. Frank et al. (2024) use this network to understand the differences in local labour market dynamics in different cities. Nedelkoska et al. (2018) also use O*NET data but focus on occuaptions' knowledge, skills and abilities (KSA) to create a 'KSA-space' of occupations. They argue that their network captures how workers can move between occupations better than one based on occupation tasks, because KSAs relate to the generality of jobs and the ability to learn certain concepts, while occupational tasks focus more on an occupation's specificity. Studies that apply skill networks to green and brown jobs include Bowen et al. (2018), who use O*NET's list of Career Changers, which connects occupations to other occupations based on whether it is a likely career move. They find few direct transition options between green and brown jobs, suggesting that 'greening' the workforce will take multiple stages of retraining.

Others have studied networks where nodes are skills rather than occupations. Alabdulkareem et al. (2018) find a strong polarization in the co-occurrence network of skills in occupations. Their 'skillscape' network correlates highly with educational requirements and wages, and their results suggest how skill differences can lead to more workforce polarization. Conversely, Hosseinioun et al. (2024) find a *nested* structure of skills. More nested skills, which build on prerequisite skills, lead to higher wage premiums. However, to reap the benefits of more nested skills, it is critical to keep enhancing foundational skills, too. Taking a somewhat different approach, Neffke (2019) creates different networks of educational tracks based on their co-occurrence in firms and the correlation over all workers in an occupation. This allows them to make the crucial distinction between the substitutability and complementarity of occupations.

Other labour market networks The effect of *social networks* on labour outcomes is well known – people often learn about job opportunities via their relations (Granovetter, 1974; Montgomery, 1991; Jackson et al., 2021). Gore and Hollywood (2009) found that this was also important for the employment perspectives of displaced coal workers in the UK. In his seminal networks paper, Granovetter highlights the importance of 'weak' ties, edges that connect individuals outside of their core relations (Granovetter, 1973). These edges often expose people to a larger variation of job opportunities than their stronger links (Zenou, 2015).

In a very different approach, Hartmann et al. (2019) start from a bipartite occupation-industry network, using Brazilian data on what occupations are often employed by which industries. To study social stratification, they create a one-mode projection of occupations that are linked if they are often co-employed in an industry. Using a similar technique, Muneepeerakul et al. (2013) define a network of occupations, where edges are location co-occurrence probabilities.

Finally, a network approach is sometimes implied but not explicitly discussed.

For an overview of non-network science approaches to occupational mobility, for example, see Cardoso and Hartmann (2023).

1.3.4 Networks of structural change

In Paper 3, we put our work on skill intensity in the context of the product space of Hidalgo et al. (2007). The product space is a network of products; two products are connected if countries often export both of them. The product space is thus the one-mode projection of the country-product bipartite network. The edges can also be interpreted as empirical conditional probability: the edge weight between two products is the probability that one of them is exported competitively by a country, given that the other is as well.[5] While countries have vastly different development and industry diversification trajectories (Lall, 2000), the product space unveils universal patterns of diversification at highly disaggregated product levels (Hidalgo et al., 2007).

The product space has spawned a lively research field with many subsequent networks papers, including some on the green transition. Mealy and Teytelboym (2022) define the *Green product space* as a subset of the product space consisting of only green products. Luo et al. (2024) do the same with a more limited set of renewable energy products and find path-dependent diversification in their network. Andres et al. (2023) additionally label *brown* products and identify potentially *stranded* diversification pathways in the product space that will become obsolete as the green transition gets underway.

The underlying ideas of path dependence in regional development have a much longer history in economics in the literature of spillovers and agglomeration externalities. In particular, discussions of Marshallian and Jacobs spillovers have dominated this field. In their seminal framework, Marshall (1890) explained that co-locating firms save cost based on similarities in logistics (supply chain linkages), hiring (hu-

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[5] This is made symmetric by taking the minimum value of both products.

man capital similarities), and know-how (technological overlap). More similarities would drive firms closer. Ellison et al. (2010) find support for all three channels, especially supply chain linkages. Bahar et al. (2019) also point to the salience of supply chain linkages. Others, conversely, have shown that the importance of supply chain relationships has decreased over the past decades in favour of skill similarities (Diodato et al., 2018) or technological overlap (Steijn et al., 2022). But supply chain linkages may still matter if technological overlap is important (Juhász et al., 2024).

While Marshallian spillovers concern firm co-locations in the same industry, Jacobs spillovers, by contrast, are innovations that spill outside of a particular industry (Jacobs, 1969; Rosenthal and Strange, 2004). Li and Neffke (2024) show that weighing by industry size improves size and entry predictions of related activities, indicating that the principle of relatedness – discussed earlier – may be more aligned with Marshallian than Jacobs spillovers.

Recent empirical network studies have started connecting regional development networks with labour market data. Diodato et al. (2022), for example, find that new industries are more likely to develop in a country if they require fewer 'new occupations' to combine with the existing labour force. Similarly, Johnson (2020) uses a network of industries connected by occupational similarity. This network is informative about the diversification of countries into new industries.

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2 Interlocking path dependencies in green industrial strategy

Short title: Path dependencies in green industrial strategy

Joris Bücker[1,2,*], Penny Mealy[1,2,3,4]

[1]Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK.

[2]Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK.

[3]Santa Fe Institute, Santa Fe, NM, USA.

[4]SoDa Labs, Monash Business School, Melbourne, Victoria, Australia.

[*]Corresponding author. Email: joris.bucker@seh.ox.ac.uk

Green industrial strategy has grown in popularity, both in policy practice and the economic literature. In this work, we use network science to expose path dependencies in green industrial policies targeting products in the value chain of three major renewable energy technologies: solar PV, wind energy, and batteries for electric vehicles. We show that the number of these green industrial policies has grown from approximately 10% of all industrial policies to 20% between 2010 and 2022. This trend is remarkably stable across the country income spectrum. We introduce three industrial strategy networks of countries, products, and policy instruments based on their co-occurrence in the industrial strategy data. The network structure conditions the adoption of new policies, which tend to a) use policy instruments that are close in the policy instrument network to earlier-used instruments, b) target products that are related to previously-targeted products, and c) replicate policies of related countries.

Teaser

The network structure of industrial strategy conditions countries' growing green industrial strategy ambitions.

Introduction

Green industrial strategy[1], which aims to incentivize structural change towards low-carbon technologies and sectors, has recently grown in popularity as a tool to accelerate decarbonization while stimulating economic growth. Green industrial strategy is part of the decarbonization plans of high-income countries (Kleimann et al., 2023), as well as those of low- and middle-income countries (Lewis, 2021). Due to the nature of climate change, the case for green industrial strategy is often seen as stronger than industrial strategy more generally (Hallegatte et al., 2013; Harrison et al., 2017), as it tackles environmental externalities as well as knowledge externalities Rodrik (2014). Green industrial strategy can also bring co-benefits, such as gaining international market share in green products and a more resilient green value chain.

While green industrial strategy has become central to climate and economic policymaking (Meckling, 2021), its dynamics and direction are still poorly understood (Evenett et al., 2024). Green industrial strategy can help overcome important barriers slowing down the energy transition (Jakob and Overland, 2024). However, a wide variety of green industrial strategy options exist, and new policy adoptions affect politicians, institutional capacity, and interest groups, among other things, leading to further policymaking via complex feedback loops (Pierson, 1993; Béland, 2010; Hall, 1993; Evenett et al., 2024; Juhász and Lane, 2024; Reichardt et al., 2016; Hoppmann et al., 2014; Eskander et al., 2024). Some of these new policies will work counterproductively (Jakob and Overland, 2024). Evidence on the sequencing and path dependencies in green industrial strategy can thus help inform policymakers of the barriers and expectations of new policy adoption (Linsenmeier et al., 2022; Fankhauser et al., 2016). As future industrial strategy shifts further towards green

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[1] We use the term 'industrial strategy' for the type of policies that Altenburg and Rodrik (2017) call *structural transformation policies* or *productive development policies*. These are more conventionally referred to as 'industrial policies', which we use when discussing specific policies or policy adoptions.

industrial strategy, understanding these dynamics will be crucial for future decarbonization momentum.

This paper contributes to understanding the structure and path dependence of green industrial strategy along its three main dimensions: the countries that implement it, the products it targets, and the policy instruments it uses. Spillovers in climate policy can greatly impact future climate change action (Juhász and Lane, 2024; Linsenmeier et al., 2023). But while the literature has studied how policy diffusion happens between local or national governments (Berry and Berry, 1990; Fankhauser et al., 2016), much less attention has been given to spillovers in the product and policy instrument dimensions. After discussing new stylized facts for the 2008–2022 study period, we use network science methods to build on the hypothesis that path dependencies can make (green) industrial strategy – to some extent – predictable and aid in our understanding of future green industrial strategy.

Our study makes four contributions to the study of green industrial strategy. First, we provide a new database of green industrial strategy covering the period from late 2008 to early 2022, comprising policies that incentivize the local manufacturing of products in the value chain of three major renewable energy technologies: wind energy, solar PV, and electric vehicle (EV) batteries. These are proven technologies that will likely play a significant and crucial role in the energy transition (IEA, 2024b,a), and their value chains take central positions in the critical minerals and supply chain resilience debate (IEA, 2021).

While country-level studies have produced high-quality data, a fundamental challenge when trying to understand industrial strategy spillovers is the lack of datasets covering global (green) industrial strategies (Evenett et al., 2024). New data-gathering efforts have started addressing this but often lack longitudinal depth. For example, the New Industrial Policy Observatory (NIPO) dataset aims to track industrial strategy from 2023 onward (Evenett et al., 2024). The OECD's Quantifying Industrial Strategies (QuIS) database includes industrial policies between 2019 and 2021. The OECD also published the post-COVID (2020 onward) Low Carbon Technology Support (LTCS) database, part of which can be regarded as green industrial strategy (Aulie et al., 2023).

Our approach is to combine two distinct datasets: the industrial policies collected by the global trade alert (GTA) initiative (Evenett, 2009) and a list of renewable energy value chain products from Rosenow and Mealy (2024). A dataset most related to ours is that of Juhász et al. (2022), who also use GTA data but exclude policies that do not have a clear industrial strategy objective. Our data, conversely, comprises any policy within the GTA scope that affects the green energy value chain, including those that do not explicitly mention this objective. See Materials and methods for more details.

Our second contribution is to give new insights into the growth and spread of green industrial strategy (Juhász and Lane, 2024). The fraction of green policies of the total grew from around 10% in 2010 to 20% in the early 2020s, matching the results of Criscuolo and Lalanne (2024) in the very different QuIS dataset, who find that about 15% of industrial policies are green. While high-income and large middle-income countries are implementing most policies, we find that the rate of green industrial policies is remarkably constant across countries.

A diverse set of instruments are included in industrial strategy. Felipe (2015) identifies eight categories of industrial strategy instruments: fiscal incentives, investment attraction programs, training policies, infrastructure support, trade measures, public procurement, financial mechanisms, and industrial restructuring schemes. GTA identifies more than fifty individual instruments. Consistent with the literature, we find that low-income countries tend to rely more on import tariffs and other import controls, while high-income countries use subsidies and other non-tariff instruments more often (Evenett et al., 2024). Non-tariff instruments come in many forms and are growing in prevalence. For example, local content requirements are widely used in green industrial strategy (Mathews, 2020; Lewis, 2021; Scheifele et al., 2022). Often, countries use a multi-pronged strategy with multiple policies and instruments (Lee, 2020; Lewis and Wiser, 2007).

Our third contribution is to explore the mix of industrial strategies in different countries using network science. Each industrial policy is implemented by a country, targets certain products, and uses a specific policy instrument. We use the economic geography method of *relatedness* (Hidalgo et al., 2018, 2007) to create three networks of 180 countries, 4,583 products, and 42 instruments, respectively, which are linked based on how often they co-occur in the data.

The networks give new insights into the structure of industrial strategy, for example by finding clusters of instruments that are frequently used together, and by highlighting which policy instruments are predominantly used for upstream products, such as export taxes, versus downstream products, such as local content requirements.

The network structure is a solidification of the complex evolving process of policymaking. Governance capacity, including lack of political will or financial, bureaucratic, and informational constraints, can limit the available policy options (Juhász and Lane, 2024; Felipe, 2015; Mealy et al., 2024). Conversely, recurring patterns of policy sequencing over the study period strengthen connections in the networks (see, e.g., Lebdioui (2022) and Lee (2020) for case studies on how industrial strategy was sequenced in Malaysia and Korea, respectively). In all, the networks show how these and other processes and barriers have conditioned industrial strategy over the study period.

Our fourth and final contribution is demonstrating that the industrial strategy networks contain useful information about the adoption of new green industrial policies. We show that new policies are more likely to be adopted if they are aligned in the networks with earlier policy introductions. Thus, policymaking exhibits a form of path dependence on the three dimensions.

This result builds on several strands of existing work relating to the three industrial strategy dimensions. First, most clearly established in the literature is the country-to-country diffusion of (environmental) policies across geographical borders, trade routes, via membership of international organizations, and other channels (Walker, 1969; Kammerer and Namhata, 2018; Linsenmeier et al., 2023; Fankhauser et al., 2016; Graham et al., 2013; Jordan and Huitema, 2014). For some countries, a substantial portion of future emission reductions of a carbon pricing mechanism may come from the secondary policy diffusion effect it has on *other* countries implementing carbon pricing (Linsenmeier et al., 2023). Examples of drivers of policy diffusion include policy learning – for example to understand and replicate the successes of East Asian countries in the 1960s and beyond (Aiginger and Rodrik, 2020; Lall, 2003) – as well as shared (geopolitical) trends such as a rising inclination for industrial strategy addressing climate change, supply-chain resilience, and national security (Evenett et al., 2024). Tit-for-tat mechanisms can also induce countries to reply in kind and replicate each other's industrial policies (Evenett et al., 2024).

Second, certain policy instruments can build institutional capacity that is helpful for adopting other instruments (Linsenmeier et al., 2022; Mealy et al., 2024; Juhász and Lane, 2024), as the multi-dimensionality and nestedness of institutional capabilities can lead to path dependencies (Wu et al., 2015; Clar et al., 2013; Mukherjee et al., 2021). Particular policy instruments can also help overcome political barriers to further policymaking. Indeed, the role of green industrial policy instruments as a precursor to other environmental policies is a further reason why green industrial strategy is viewed more favorably than industrial strategy in general (Juhász and Lane, 2024; Linsenmeier et al., 2022; Mealy et al., 2024; Meckling et al., 2017). This is particularly true regarding carbon pricing, which is often seen as one of the most effective climate change policies but has been met with high political barriers (Blanchard et al., 2023; Jakob and Overland, 2024; Meckling et al., 2017; Linsenmeier et al., 2022; Stiglitz, 2017; Carattini et al., 2018).

Third, earlier studies have pointed to natural orderings or groupings of products that countries (can) target with industrial strategy, for example products connected in the same value chain (Hirschman, 1958; Lebdioui, 2022), or those that require the same skills (Schetter et al., 2024) or other capabilities (Hidalgo et al., 2007; Zaccaria et al., 2014; Surana et al., 2020). Industrial strategy may try to leverage these path dependencies or expand towards other paths (Hidalgo, 2023). Technological complementarity can also play a role. For example, to qualify for subsidized loans from BNDES, Brazil's national development bank, wind energy projects in Brazil had to comply with local content requirements that covered progressively more parts of the wind turbine over time. In 2012, at least one of four major wind turbine components – tower, blade, hub, and nacelle – had to be produced locally; by 2016, all of them had to be (Bazilian et al., 2020). This gave local manufacturers the time to develop the capabilities for more complex parts, while having a stable domestic demand for the less complex ones.

The rest of this paper is structured as follows: We start by discussing our results. First, we examine green industrial strategy trends in the 2010s. Then, we introduce our industrial strategy networks and show their role in conditioning the adoption of new policies. We conclude by situating our results in the policy innovation and diffusion literature.

Results

Classifying green industrial strategies

In this study, we deem industrial strategy *green* if it affects the value chains of three key renewable energy products – wind energy, solar PV, and batteries. These are proven renewable energy technologies that will likely play a significant and crucial role in the energy transition (IEA, 2024b,a), are expected to expand rapidly worldwide, and are at the center of debates on critical minerals and supply chain resilience (IEA, 2021). See the Materials and methods section for a further discussion on how our definition of green industrial strategy relates to other such definitions.

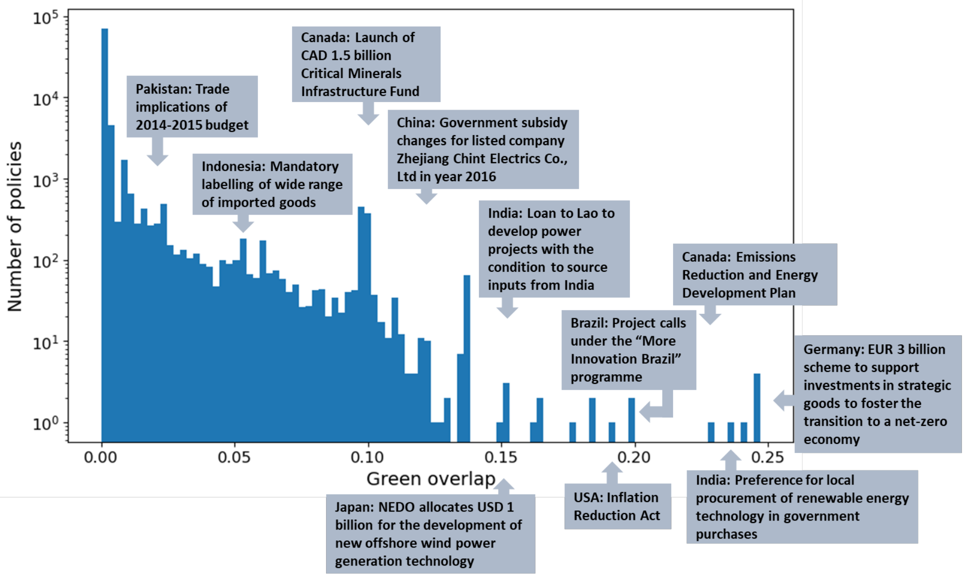

Figure 1: **Green overlap of all industrial policies.** Histogram of overlap between the products targeted by industrial policies and those in the renewable energy value chain. Note the logarithmic scale on the vertical axis.

Many green industrial policies target a variety of products beyond the green value chain too. We therefore define the *green overlap* r_i of policy i as the overlap between the green value chain products and products targeted by policy i (see Materials and methods for more information). In Fig. 1, we show the distribution of green overlap in our dataset. Most policies have no or only a small green overlap. The callout boxes highlight selected policies at different green overlap values. Policies with a high green overlap have clear climate action goals, such as Germany's support for "investments in strategic goods to foster the transition to a net-zero economy" ($r = 0.24$) and Japan's New Energy and Industrial Technology Development Organization (NEDO) allocating 1 billion USD for the "development of new offshore wind power generation technology" ($r = 0.15$). Policies with a lower but nonzero green overlap are more generic, such as Indonesia's mandatory labeling of a wide range of imported goods ($r = 0.05$), or motivated by related goals, such as Canada's launch of a 1.5 billion

CAD "Critical Minerals Infrastructure Fund".

We call any policy with a nonzero green overlap a *green industrial policy*. These policies target at least one green product.

Green industrial strategy on the rise

The number of green industrial policies has grown in absolute numbers and as a fraction of all active industrial policies. Fig. 2A shows that the total number of active policies has grown almost linearly throughout the study period.[2] The number of green industrial policies has grown even faster. The mean fraction over all countries of green industrial policies has roughly doubled, from 10% in 2010 to 20% in 2020 (Fig. 2B).

Fig. 2C shows that the propensity to introduce green industrial policies is highest for high- and upper middle-income countries. Remarkably, however, the rising trend in the share of green industrial policies is common and consistent among all income groups, as can be seen in Fig. 2D.

The dominance of high- and upper middle-income countries in the data is evident from the map in Fig. 2E. The top nine countries by number of green policies include four European countries plus the US, Canada, Russia, China, and India. This primarily reflects these countries' propensity to use industrial strategy in general, as shown in Fig. 2F.

Our detailed data enables us to project the trajectories of countries' active policies over time on specific renewable energy technologies or in a particular stage of the green value chain. Each green product in our data can be classified as end product, sub-component, processed material, or raw material of either wind energy, solar PV, or EV batteries (see Rosenow and Mealy (2024) for details). The top panels of Fig. 3 show that, over time, China and the US have the most active policies in all

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[2] This growth is partly an artifact of the data: We do not know what policies were implemented before late 2008 and how many of these old policies were still active or discontinued during the study period. This does not affect the *fraction* of green policies.

three green technologies' end products, while Germany took the leading position in wind energy policies for several years. Other countries are catching up. For example, Brazil has quickly increased the number of policies targeting wind energy end products between 2020 and 2022.

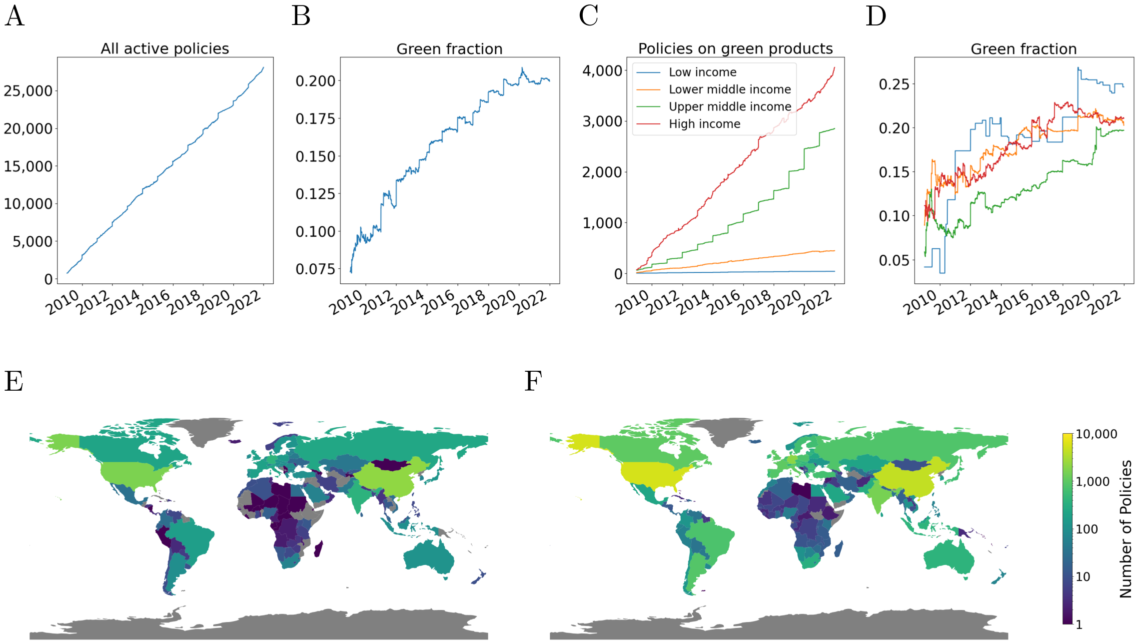


Figure 2: **Global use of (green) industrial strategy between late 2008 and 2022.** (A)–(D) Number of active policies over time. In (A) the total number of active industrial policies; (B) the fraction of green industrial policies to all industrial policies, average by country; (C) the number of active green industrial policies, split by country income group; and (D) the fraction of green industrial policies, average by country and split by country income group. (E)–(F) Maps of countries colored by the number of industrial policies introduced between late 2008 and 2022 targeting (E) at least one green product and (F) any product. Note the logarithmic color scale.

The bottom panels of Fig. 3 focus on the technologies' upstream value chain by looking at the raw materials, processed materials and sub-components combined, excluding end products. The gap between the most prolific countries and the rest is wider for the upstream value chain than for the end products. China had most active policies applied to products in the EV and solar PV value chains in the early 2020s, and the US on the wind energy value chain. Japan, Germany, and India take a distant third place in EV, solar, and wind, respectively.

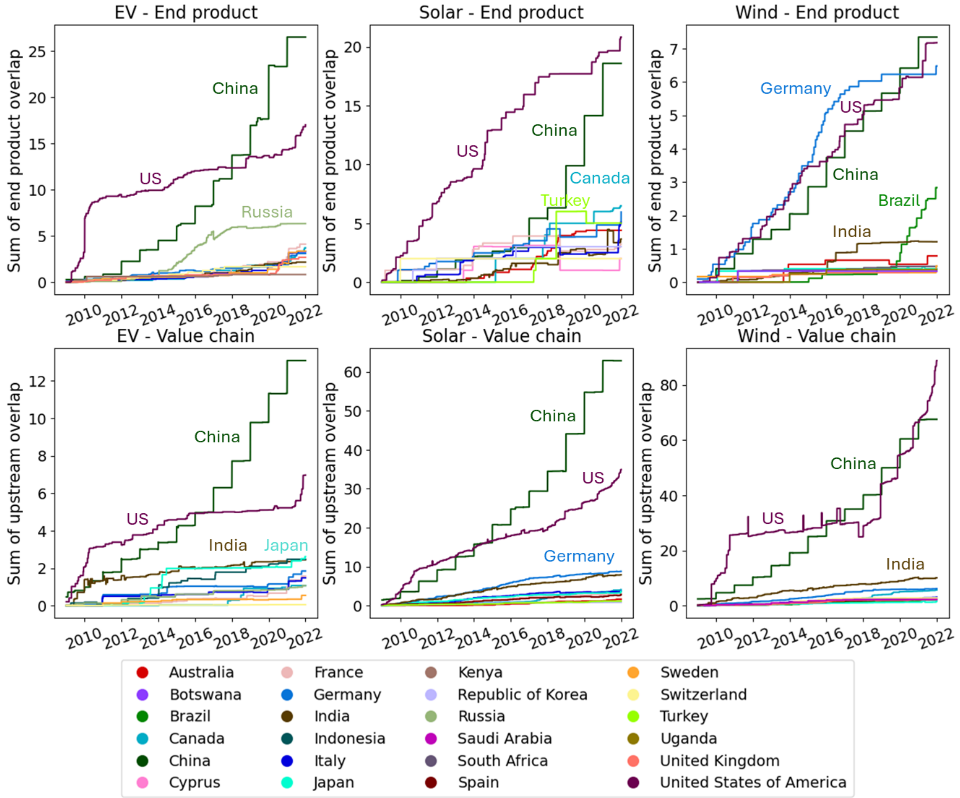


Figure 3: **Policy activity over time for selected countries.** Individual countries' sum of green overlap of active policies on each technology (left to right) and acting on end products (top) or the rest of the value chain (bottom). Only the top 15 countries for each technology in the 2020–2022 period are shown.

In this section, we have highlighted stylized facts of green industrial strategy. In the following sections, we show that patterns of industrial strategy can also explain new policy adoptions.

Network structure of industrial strategy

Previous studies have stressed that policymaking is a complex path-dependent process (Pierson, 2000). To understand better how this shapes green industrial strategy, we introduce three networks of industrial strategy of the 2008–2022 period, based on the co-occurrence of countries, products, and policy instruments in the data. We build on earlier notions of *relatedness* that have been used to construct networks in economic geography (Li and Neffke, 2024; Hidalgo et al., 2018; Bustos et al., 2012). In their seminal contribution, Hidalgo et al. (2007) quantify the relatedness between two products by calculating how often a country exports both products competitively and create a network of products called the *product space*.

Here, we apply a similar methodology to our industrial strategy data. We structure the data along three dimensions – implementing countries, targeted products, and policy instruments – which allows us to create three networks. Each network consists of nodes – countries, products, instruments – and edges between them that are stronger if two nodes are more *related* in their policy application. The relatedness is based on co-occurrence. For example, the relatedness between two policy instruments is larger if countries often use them both on the same products. Country and product relatedness are defined analogously. See Materials and methods for more details.

Policy instrument network

Fig. 4 shows the network of 42 industrial strategy instruments that were used by at least five countries. The network structure consists of five clusters. The *Tariffs and financial controls* cluster includes import tariffs and five financial support instruments, such as state loans. This cluster contains some of the most widely used policy instruments. Most connections out of this cluster go to the *Strategic subsidies* cluster, which consists of 13 mainly financial aid instruments with specific goals, such as production subsidies or export subsidies.

Trade controls is a cluster of ten instruments that predominantly aim to control the import and export of goods directly. It includes direct bans of imports or exports, as well as additional taxation or licensing requirements. The ten instruments in the *Local production support* cluster can be used to support local manufacturing. They can be divided further into instruments that *protect* local production by limiting imports, such as anti-dumping measures, and those that aim to *stimulate* domestic production by, for example, using local content requirements (LCRs). The final cluster is of three *Niche protection* instruments.

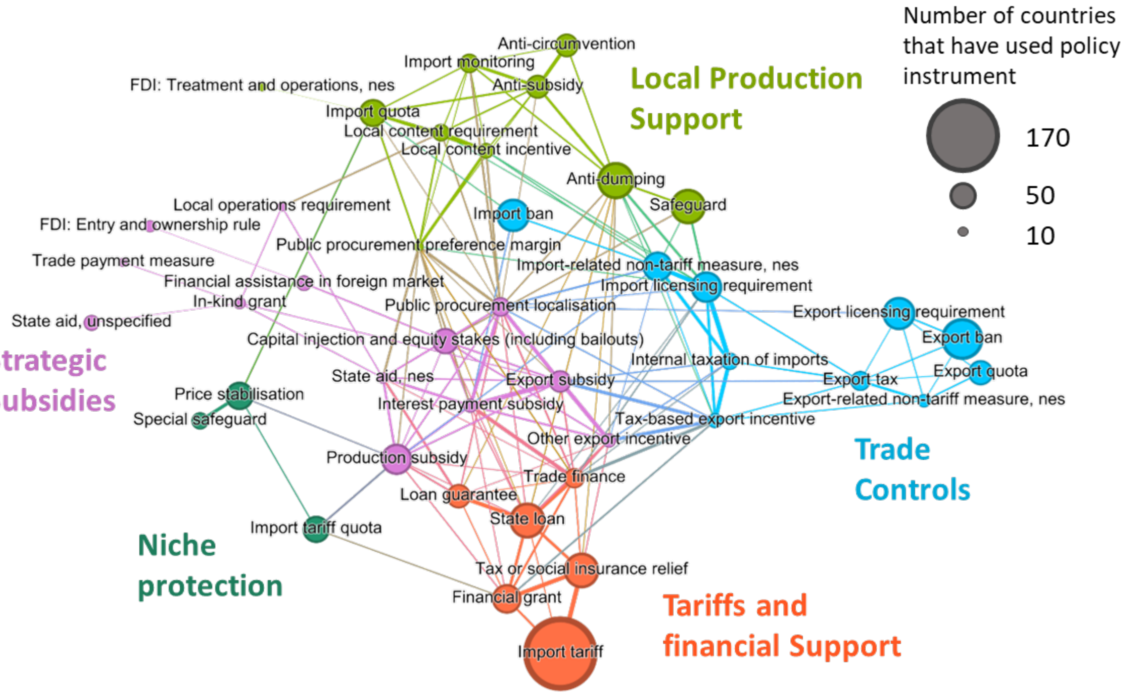
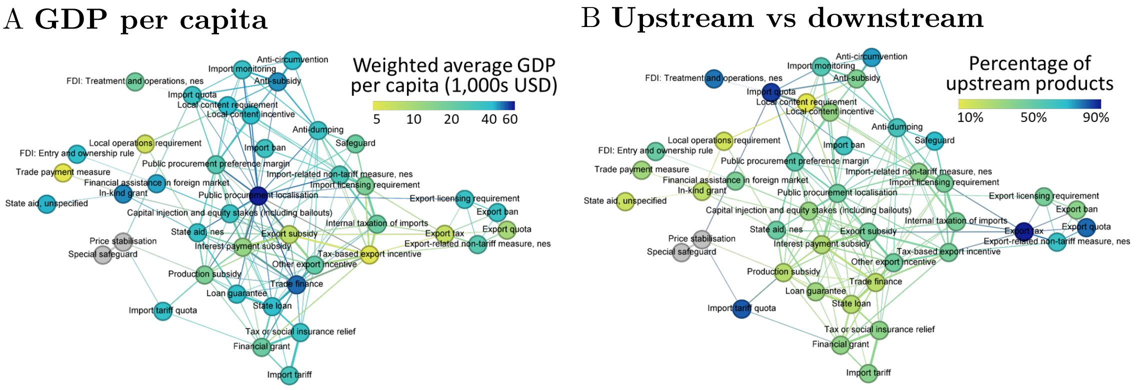


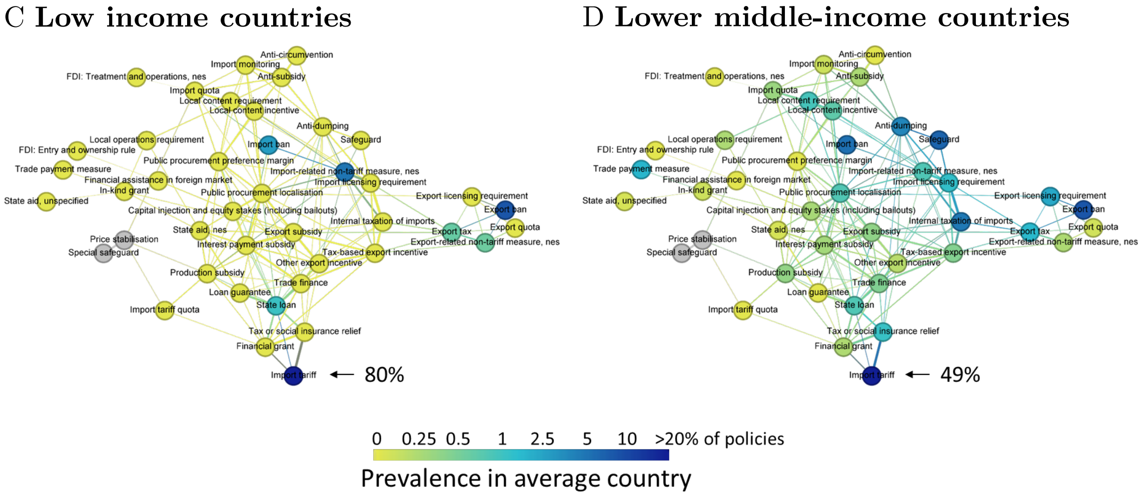
Figure 4: **Network of industrial strategy instruments.** Nodes are colored by the community structure of the full network. Some edges are removed for visualization purposes, and the network was retouched by hand to avoid overlapping nodes and labels. See Materials and methods for more information.

Countries with different income levels use other types of instruments. In Fig. 5A, we highlight for each policy instrument the weighted average GDP per capita of the countries that have used that policy for green industrial strategy. Local production support and tariffs and financial support instruments tend to be used by countries with relatively high GDP per capita values, while trade controls tend to be used by countries with lower GDP per capita. For strategic subsidies, the average country GDP value varies significantly by instrument.

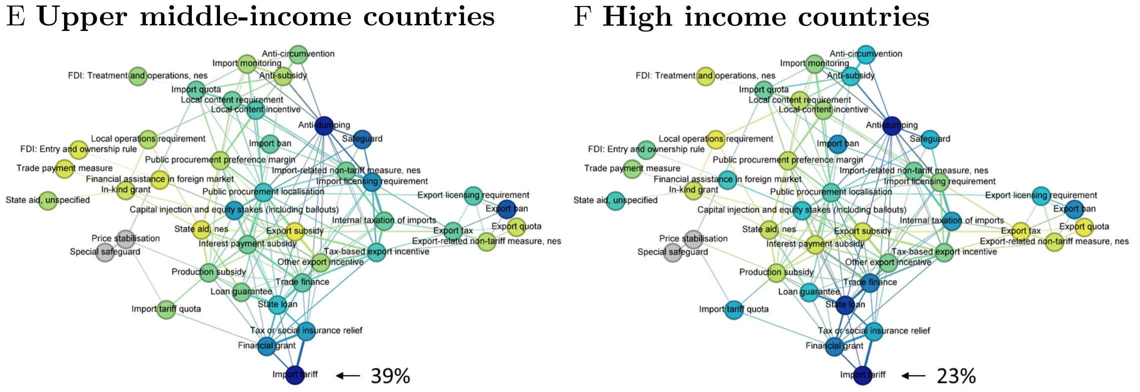
The policy instruments are also used to target different kinds of green products, such as those that are more upstream (raw- and processed materials) or downstream (sub-components and end products) in the production process. In Fig. 5B, we show that most instruments, particularly tariffs and financial aid and strategic subsidies, are used for both upstream and downstream products. However, trade controls and import quotas tend to be used more for upstream products. Interestingly, local production protection measures such as anti-circumvention and anti-dumping often target upstream products, while local production *support* measures, such as LCRs and local operations requirements, are more often applied to downstream products.


A **GDP per capita**

B **Upstream vs downstream**


C **Low income countries**

D **Lower middle-income countries**


E **Upper middle-income countries**

F **High income countries**

Figure 5: **Country and product characteristics of green industrial strategy, superimposed on the industrial strategy policy instrument network.** (A) The weighted average GDP per capita of countries using the policy instrument. (B) The percentage of products targeted with the instrument that are upstream (i.e., raw or processed materials). (C)–(F) Prevalence of instrument by World Bank Income groups. Note the logarithmic color scale.

Building on the results of Fig. 5A, we overlay on the network the propensity of different country income groups to implement the various instruments in Figs. 5C–F. Tariffs were the most-used green industrial strategy instrument by all income groups, from 80% of policies for low-income countries to 23% of policies for high-income countries. Besides tariffs, low-income countries used predominantly trade control instruments, which give direct control over the export and import of goods. Lower middle-income countries used a wider variety of instruments. While they also mainly used tariffs and trade controls, they additionally applied more local production support measures, in particular anti-dumping and safeguard measures. Lower middle-income countries also used a limited number of strategic subsidies.

Upper middle-income countries used an even wider variety of instruments, with a stronger focus on both local production support measures and tariffs and financial support. This was even more the case for high-income countries. The latter countries have also applied more strategic subsidies, such as those concerning foreign direct investment and financial assistance in foreign markets.

We thus see an expansion of the green industrial strategy toolbox from low- to high-income countries, mainly at the expense of tariffs. However, some instruments that lower-income countries often used were not or seldom used by high-income countries. For example, high-income countries did not or very rarely use some trade control instruments.

Product network

The second dimension of industrial strategy is the products that it targets. These products are not randomly chosen but result from strategic and political considerations (Juhász and Lane, 2024). In this section, we uncover relatedness patterns between the targeted products. Analogously to the industrial strategy instrument network, we create a network where the nodes are products and the edges between them represent their relatedness in the policy data. The relatedness between two products is high if countries often target both products with the same instrument. We include all products here, not just green products. Fig. 6A shows how the network groups together products by aggregate product categories.[3] This is not necessarily a surprise. Policies often cover multiple products from the same industry, increasing their relatedness.

The network has a core-periphery structure; most products are in the core. In general, products in the periphery have been used by more countries, although this is not true for mineral products. Different parts of the periphery have been targeted by a different mix of policy instruments or by different countries. By contrast, products in the network's core have seen relatively few countries targeting them with relatively few different policy instruments.

Figs. 6B and 6C highlight the green value chain products in the network. Green products are overrepresented in the network's periphery and thus tend to have received more policy attention than other products. Fig. 6B shows that the products from the different value chain stages are primarily present in different network parts. This is particularly true for raw materials and processed materials, which are predominantly grouped in the left-side peripheral communities of mineral products and metals, although some processed chemicals are located in the core. Sub-components are relatively spread out but inhabit mainly the bottom right parts of the core and periphery, where products in machinery, electronics, chemicals, and plastics are located. End products are much fewer but tend to be located in the same area. Comparing Figs. 6B and 6C, green products are grouped more by their value value chain position than their associated renewable energy technology.

These results indicate that while countries tend to target certain industries together, they usually do not focus on all products of one renewable energy technology. Instead, they are more likely to focus their policies on one part of the value chain covering different technologies.

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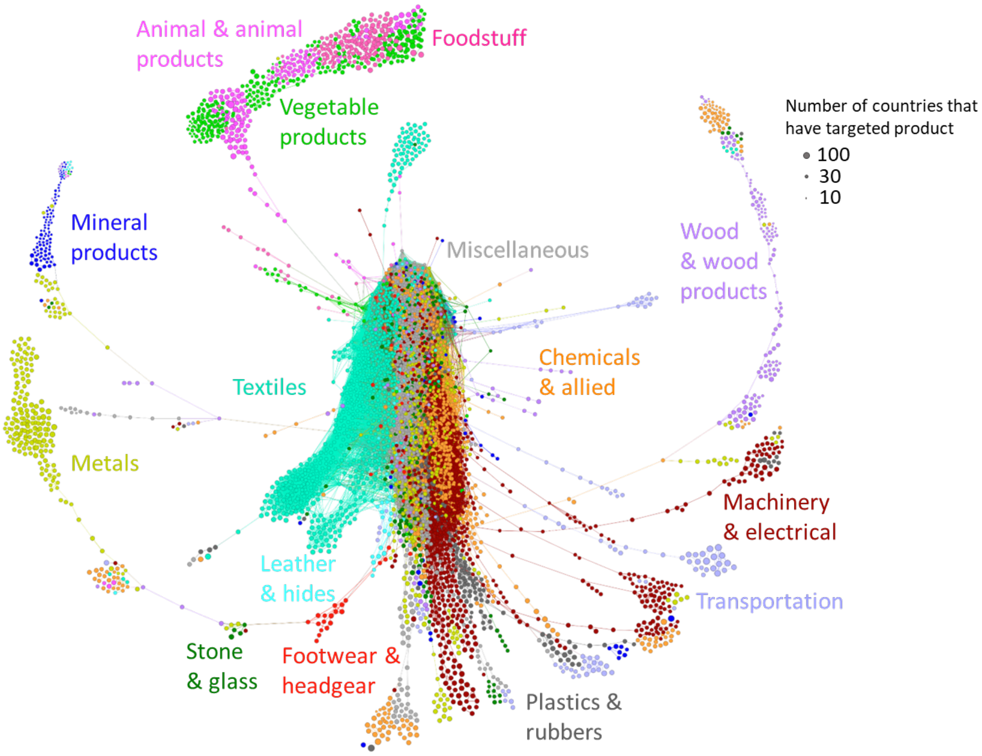
[3] See Supplementary Materials Table S1 for a list of product categories and their associated HS codes.

A **Product category**



B **Value chain position**

C **Renewable energy product**

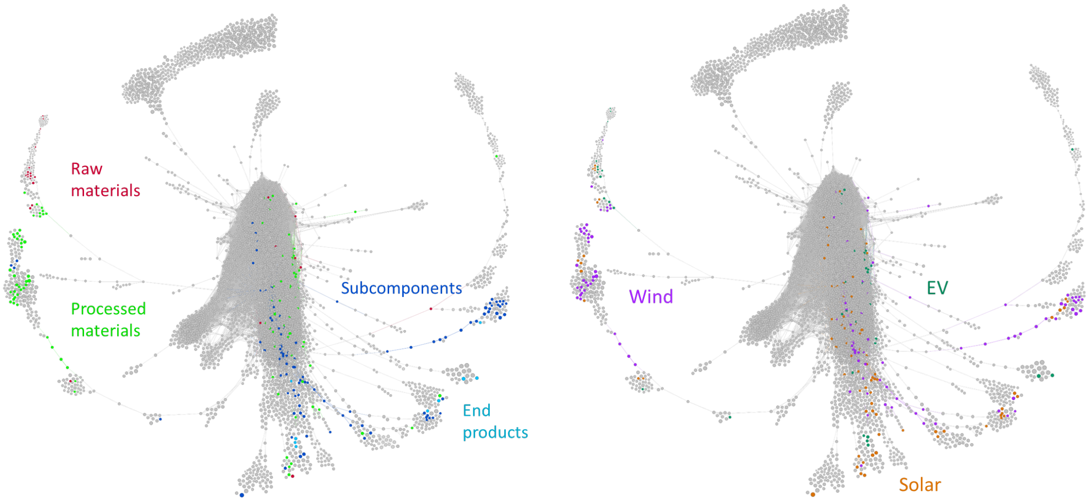


Figure 6: **Product network.** The products are colored by (A) their aggregate product classification, (B) their position in the green value chain, and (C) their associated renewable energy technology. Non-green products are colored gray.

Country network

Finally, Fig. 7 shows the relatedness network of countries. Two countries are related if their industrial strategy overlaps in terms of the products targeted and instruments used. This network connects to the literature on policy diffusion from country to country (Walker, 1969; Linsenmeier et al., 2023; Kammerer and Namhata, 2018; Fankhauser et al., 2016; Graham et al., 2013; Jordan and Huitema, 2014).

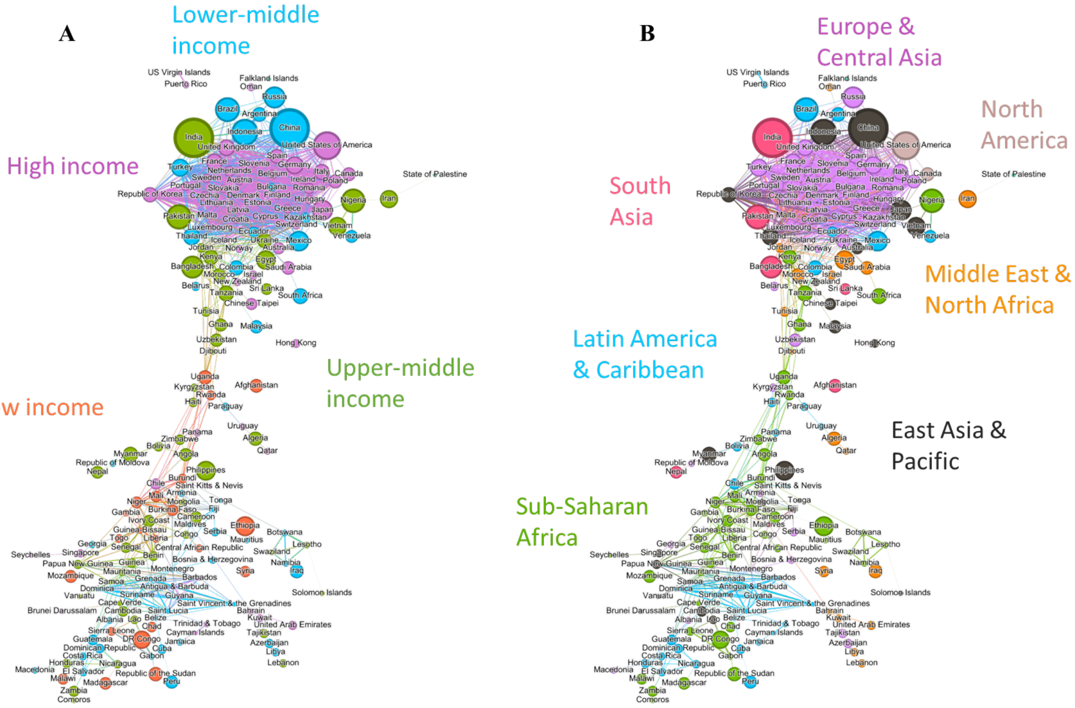


Figure 7: **Country network.** Size indicates total population. The countries are colored by (A) the World Bank income classification and (B) geographical region. The layout is adjusted to minimize overlapping nodes and labels.

At the top of the network, populous countries that produce many policies, such as India, China, Brazil, and the US, cluster together. Directly below is a dense group of almost all European countries, with certain middle-income countries, such as Pakistan, Thailand, Vietnam, and Nigeria, directly adjacent. These countries form a strong cluster of related industrial strategy.

The rest of the countries in the less dense lower part of the network tend to be grouped by income status and geographical region, echoing earlier results in the literature (Fankhauser et al., 2016; Graham et al., 2013). While not a perfect clustering, one can make out groups of Sub-Saharan countries in the lower center of the network, West and Central Asian countries on the bottom right, and Central American countries on the bottom left.

Path dependence of new policy adoptions

The three networks introduced above describe different dimensions of the underlying structure of industrial strategy. We know from the literature that policies build on and react to earlier policies through a complex process involving their stakeholders and interest groups and by building institutional capacity (Pierson, 2000; Béland, 2010; Meckling et al., 2017). Internationally, policies 'diffuse' across international borders (Graham et al., 2013; Fankhauser et al., 2016).

In this section, we test the hypothesis that our industrial strategy networks contain information on the adoption of new green industrial policies. We use 'new' to indicate a policy consisting of a hitherto not implemented country-product-instrument combination.

Specifically, we aim to quantify to what extent countries' new green industrial policies tend to involve policy instruments and products that are 'nearby' in the networks, or policies that 'nearby' countries have implemented before. To quantify this 'nearness', we introduce a metric called *alignment* (ω), which evaluates the proximity of a potential new policy to a country's current policy portfolio or that of its network neighbors. Alignment can be measured on all three networks, and each potential new policy can thus be assigned three alignment scores: its instrument alignment ω^{instr}, product alignment ω^{prod}, and country alignment ω^{ctry}. Further details are provided in the Materials and methods section. We hypothesize that higher alignment values lead to a higher likelihood that a new green industrial policy will be adopted in the next period.

While the three alignment metrics come from different networks, the underlying dataset of policies is the same, and the information in the three alignment values can be correlated. For example, a new policy can be aligned because a related country has introduced it before ánd because it is related to a previously used instrument. The Pearson correlation coefficients in Table 1 show a moderate correlation, indicating that the three alignment metrics hold overlapping information but are largely distinct.

	Instrument alignment	Country alignment	Product alignment
Instrument alignment	1.00	0.32	0.36
Country alignment	0.32	1.00	0.40
Product alignment	0.36	0.40	1.00

Table 1: Correlation of instrument, country, and product alignment.

We use a probit regression model to quantify the effect of alignment on the adoption of new green industrial policies. We split our data in two. We use the first half, between 2008 and 2016, to build the industrial strategy networks. We use these networks to calculate the alignment of all potential new policies in all countries at the start of 2016. In the second half of the data (2016–2022), we tally what new green industrial policies were actually introduced by the countries. Specifically, we set the variable $PolicyAdoption_{pci}^{\text{green}} = 1$ if at least one green industrial policy using instrument i was introduced in country c on product p between 2016 and 2022, and 0 otherwise. Policies already introduced in the 2008–2016 period are excluded from the data.

We then model the probability that a new green industrial policy was adopted as a function of the policy alignment. Our baseline specification is

$$P(PolicyAdoption_{pci}^{\text{green}} = 1) = \Phi\left(\beta\omega_{pci}^{\text{x}} + \gamma_c + \delta_p + \eta_i\right), \tag{1}$$

where $\Phi()$ is the cumulative distribution function of the standard normal distribution, ω_{pci}^{x} is the x-alignment of the new green industrial policy, and γ_c, δ_p and η_i are country-, product-, and instrument-level fixed effects, respectively. The fixed effects account for potential confounding factors. For example, certain countries have a higher propensity to use industrial strategy, some products are more often included in industrial strategy, and particular instruments, such as tariffs, are much more common than others.

The results are shown in Models (1)–(4) in Table 2. All alignment coefficients are positive. Instrument and product alignment are significant at the 0.1% level and country alignment at the 10% level. When all alignment variables are included in one model, the standard error increases, all coefficients become somewhat less significant, and the country alignment loses significance. The slight loss of significance confirms that the different alignment values are correlated but also hold distinct information. Taken together, the results of Models (1)–(4) show that the networks are informative of the adoption of new policies when accounting for the most direct confounding factors, although the evidence is less conclusive for the country network.

Further confounding effects may exist, however, because certain products are more salient in some countries than others. In Models (5)–(8), we therefore estimate the model

$$P(PolicyAdoption^{\text{green}}_{pci} = 1) = \Phi\left(\beta\omega^{\text{x}}_{pci} + \gamma_{pc} + \delta_{ci}\right), \tag{2}$$

where γ_{pc} are interacting country-product fixed effects, which force the model to exploit variance only between the instrument choice within a product in a country. We additionally include interacting country-instrument fixed effects δ_{ci} to exclude the effects of different instrument use patterns by different countries. Because of the more stringent fixed effects, the model can exploit variation only for around 50,000 observations.

For this model, we find all alignment coefficients individually significant at the 1% level and country alignment at the 0.1% level. A new policy is thus more likely to be introduced on a specific product in a particular country if the instrument it uses aligns more strongly with previously used instruments on that product-country pair. Together, the alignment coefficients lose some significance, especially product alignment.

Finally, we use interacting country-product(2d)-instrument fixed effects $\gamma_{cp(2d)i}$ in Models (9)–(12). These models exploit variation between products within the same 2-digit product group, within a country and specific instrument. A 2-digit product group contains all products with the same first two digits of their HS code.[4] We additionally include separate product fixed effects. These fixed effects further reduce the number of observations available for the regression to around 35,000. This specification reads:

$$P(PolicyAdoption_{pci}^{\text{green}} = 1) = \Phi\left(\beta\omega_{pci}^{\text{x}} + \gamma_{cp(2d)i} + \delta_p\right). \tag{3}$$

Dep. Var.:	Green policy adoption											
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.045^{***}			0.038^{***}	0.017^{**}			0.013^{*}	0.074^{***}			0.075^{***}
	(0.008)			(0.009)	(0.005)			(0.006)	(0.013)			(0.013)
ω^{prod}		0.028^{***}		0.022^{**}		0.137^{**}		0.067		0.237^{***}		0.168^{*}
		(0.006)		(0.007)		(0.044)		(0.046)		(0.070)		(0.075)
ω^{ctry}			0.022.	0.019			0.064^{***}	0.062^{***}			0.028^{**}	0.024^{*}
			(0.014)	(0.014)			(0.009)	(0.009)			(0.009)	(0.010)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Observations	1,285,370	1,285,370	1,285,370	1,285,370	51,252	51,252	51,252	51,252	34,849	34,849	34,849	34,849
Pseudo R^2	0.385	0.384	0.381	0.388	0.402	0.402	0.405	0.405	0.418	0.415	0.415	0.419

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*
Fixed effects: C, country; P, product; P(2d), product groups of same two starting HS digits; I, instrument; a dash '-' indicates interacting fixed effects

Table 2: Effect of policy alignment on new green industrial policy adoptions. Policy alignment is calculated on data between 2008 and 2016. New green industrial policy adoptions were observed between 2016 and 2022. The table reports standardized regression coefficients and clustered standard errors.

Table 2 shows that instrument alignment and product alignment are significant in this model at the 0.1% level and country alignment at the 1% level. Together, they remain positive and significant at the 5% level. These results show that products in a specific industry in a country that are more aligned with the new green industrial policy's instrument are more likely to see that policy adopted.

Together, our results provide evidence for the general tendency of countries to implement novel policies that are more aligned with their existing policy portfolio (according to our networks). The evidence is particularly strong for instrument alignment. In the Supplementary Materials Section C.1, we additionally include

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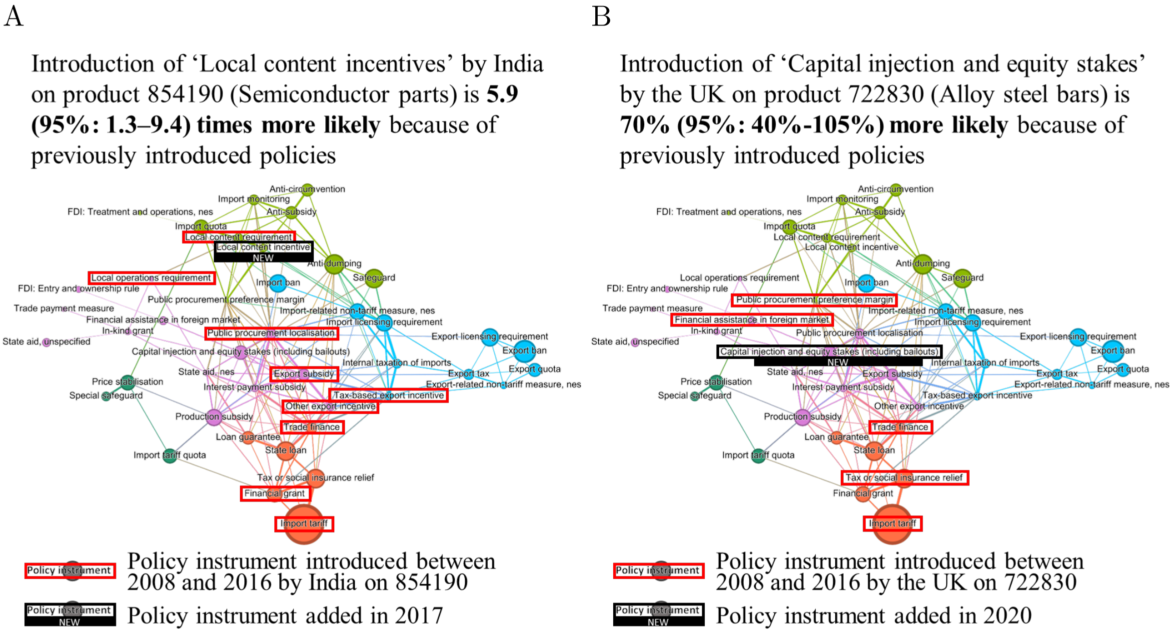
[4] There are 96 2-digit product groups in the full HS92 classification; 29 of them contain green products.

results for all industrial policy adoptions, rather than solely *green* ones. The results are qualitatively similar, except that the product alignment coefficient turns negative but insignificant in Models (4) and (12). In Section C.2, we do a further robustness analysis with a linear probability model rather than a probit model. This results in positive and highly significant coefficients for all alignment metrics in all specifications, confirming our main results. In Section C.3, we additionally show results for changing how we split our data between a network formation part and a policy adoption part. Setting the cutoff year to 2013 or 2019 (rather than 2016) gives fewer data to estimate the network but more policy adoptions (for 2013), or, vice versa, more data to estimate the network but fewer policy adoption data points (for 2019). While some of the coefficients in these alternative approaches have a different level of significance, virtually all coefficients are positive and support the main results of Table 2.



Introduction of ‘Local content incentives’ by India on product 854190 (Semiconductor parts) is **5.9 (95%: 1.3–9.4) times more likely** because of previously introduced policies

Introduction of ‘Capital injection and equity stakes’ by the UK on product 722830 (Alloy steel bars) is **70% (95%: 40%-105%) more likely** because of previously introduced policies

Policy instrument introduced between 2008 and 2016 by India on 854190

Policy instrument added in 2017

Policy instrument introduced between 2008 and 2016 by the UK on 722830

Policy instrument added in 2020

Figure 8: **Counterfactuals of policy adoption likelihood**. Two examples of how much more likely a policy instrument adoptions became for a country-product pair because of earlier implemented policy instruments: (A) India and solar PV value chain product 854190, and (B) the UK and wind energy value chain product 722830.

While Table 2 shows the positive and statistical significance of the alignment metrics, the effect size can be hard to interpret from the regression coefficients, especially for a nonlinear probit regression. Therefore, we show in Fig. 8 two examples of new policy adoptions and how much more likely they were to be implemented because of their alignment with the existing policy portfolio. These two examples are calculated with the results of model (1) in Table 2 (see Materials and methods for more details). They thus only use the information from the policy instrument network.

In Fig. 8A, we have highlighted in red the industrial strategy instruments that were introduced by India between 2008 and 2016 targeting solar PV value chain product 854190 (Parts of semiconductor devices and similar devices). Compared to a counterfactual situation where no other policy instrument had been introduced on this product, the introduction of 'Local content incentives' was 5.9 times more likely because of the network effects. India added this policy in 2017.

Another example is shown in Fig. 8B, where we overlay the instrument network with the policy instruments that the UK introduced between 2008 and 2016 on product 722830 (Bars and rods of alloy steel (other than stainless), hot-worked), which is a wind energy product. Compared to a situation in which no other policy instrument had been introduced to this product, the introduction of 'Capital injection and equity stakes (including bailouts)' was 70% more likely because of the network effects. This policy was added in 2020.

Discussion

This study contributes to a growing body of research on green industrial strategy. Our results uncover path dependencies in green industrial strategy along three dimensions: A country is more likely to pursue new policies if they align with products previously targeted, instruments previously used, or if related countries have implemented them before. We quantify alignment and relatedness using methods from network science.

Our study makes four main contributions. First, we present a new database of green industrial strategy. This data comprises industrial policies implemented between late 2008 and 2022 in the value chains of three major renewable energy technologies: solar PV, wind energy, and EV batteries. The data is the subset of the global trade alert (GTA) data (Evenett, 2009) that acts on the renewable energy value chain products gathered by Rosenow and Mealy (2024). We believe this data can be an asset for the research community in helping to understand the trends and patterns in green industrial strategy. Second, we provide stylized facts of green industrial strategy during the 2010s. Among other things, we find that the mean share across countries of active green industrial policies has been rising steadily from about 10% of policies in 2010 to 20% in the early 2020s. This trend is remarkably consistent across country income groups. Third, we propose three dimensions of industrial strategy – countries, products, and policy instruments – and explore their network structure using methods from economic geography. Fourth, we show that countries are more likely to pursue new policies if they align with their policy portfolio according to the industrial strategy networks.

Our paper does not study the causes of path dependence, but we can relate our three networks to different policy adoption drivers identified in the literature. The policy innovation literature often distinguishes between external factors, which relate to learning and other diffusion mechanisms between countries, and internal factors, such as state capacity, political will, and cost considerations (Berry and Berry, 1990; Jordan and Huitema, 2014; Graham et al., 2013). Recent literature stresses the importance of distinguishing between political forces, which drive how industrial strategy is *chosen*, and institutional capacity, which conditions how it is *implemented* (Juhász and Lane, 2024). This leaves us with three main drivers of new industrial strategy adoption, which resemble the scope of our three dimensions: external international diffusion (country dimension), internal political drivers (product dimension), and internal institutional capacity (instrument dimension).

First, the country network shows path dependence in the external factor of international diffusion. It shows explicitly which countries overlap in their policy approach. Even if cross-border policy diffusion is well-known in the literature – including network science approaches (Kammerer and Namhata, 2018) – its understanding is still limited (Fankhauser et al., 2016; Graham et al., 2013). Mistur et al. (2023) liken policy diffusion in battling COVID-19 to the spread of the virus itself. Policy choices are shaped by policy diffusion along geographic, political, and language axes (Grossback et al., 2004; Mistur et al., 2023). Supporting these results, we find that richer and larger countries tend to cluster together, as well as countries from the same region and income group.

Second, the product network contains information on how policymakers decide what products to target with industrial strategy. Not every product can and should be targeted at once. Many strategies can be used to determine what product or groups of products to target and in what order, but this decision is a deeply political one (Juhász and Lane, 2024). Some of the patterns we find in the product network are not immediately surprising, given that the networks are based on product co-occurrence. Many industrial policies work on multiple products simultaneously, which causes related products to connect in the product network by construction. However, the predictive power of product alignment for new policy adoption suggests path dependencies exist in the network that cannot be explained by the data construction. Countries tend to target products in the same industry or that are part of the same value chain stage, but not necessarily all products that relate to the same technology.

Third, the path dependencies captured by the instrument network may to some extent be related to institutional capacity constraints. As countries gain experience with new policy instruments, they are more likely to use related instruments later on. We find clusters of policy instruments that are often used together. We also find that countries in different income groups tend to use different instruments, and that certain instruments are more often used on upstream and others on downstream products. It has been suggested that institutional capacity is multi-dimensional and nested (Wu et al., 2015; Clar et al., 2013; Mukherjee et al., 2021). Nestedness of capabilities can lead to path dependencies (Bustos et al., 2012; Mealy et al., 2024). Capabilities for export diversification have similarly been shown to be nested and path-dependent (Hidalgo et al., 2007), pointing to a possibly similar model for institutional capacity. But alternative explanations are possible. For example, a certain inertia to implement new policy instruments can also be caused by the bureaucratic minimal squawk theory (Leaver, 2009): Bureaucrats try to avoid mistakes and may thus be more hesitant to try out new instruments that are very unrelated to the ones they have used before. The minimal squawk theory could perhaps also partly explain why countries keep learning their new policy ideas from the same pool of other countries and why they tend to target related products.

We acknowledge that this mapping on the policy innovation literature is not perfect. Political constraints will, for example, also affect the choice of instrument (Juhász and Lane, 2024), and country diffusion can change the product network. Nonetheless, our mapping to policy drivers allows us to distill two further contributions of our work to this literature. First, rather than a split between internal vs external factors or political vs capacity factors, we propose a combined threefold approach for industrial strategy – international diffusion, political prioritization, and institutional capacity.

Second, while path dependence in the external factor has long been established in the literature, indeed, it is at the core of the policy diffusion narrative, the path dependence in internal factors has received less attention. We show that country diffusion cannot explain all the path dependencies in our data and that the other dimensions are sometimes more important in explaining new policy adoption. While some mechanisms of path dependence in the internal factors have been explored in the literature, future research can work on a unified framework to further our understanding of the drivers of industrial strategy path dependence, or it can build on our methods to find path dependence in other fields of policymaking.

The interlocking path dependencies in our study can imply frictions or inertia when trying to adopt new policies. Policies that worked well in one country or on one product may fail to get implemented in other, unaligned contexts. Pursuing industrial strategy beyond a country's institutional capacity can fail (Juhász and Lane, 2024). On the other hand, understanding the network structure of industrial strategy can help countries harness the path dependencies. When designing new policies, it is good to be mindful of these risks and opportunities.

Our framework cannot explain every policy adoption; many other factors, such as idiosyncratic characteristics of policy instruments or products, also play a role. For example, medium complex technologies, such as wind power technology and EVs, may be relatively good bets for industrial strategy (Malhotra and Schmidt, 2020). But mass-produced goods, such as solar PV, may face a first-mover disadvantage that can undermine longer-term competitiveness (Peters et al., 2012). Conversely, too complex or customized green technologies, such as nuclear energy or BECCS installations, may face too high learning barriers, even with strong policy support (Malhotra and Schmidt, 2020).

Additionally, economic circumstances change constantly, and so will the most appropriate policy (Stiglitz, 2017). Policies that our framework deems less likely to get adopted should, therefore, not be discarded outright. Instead, it can be a starting point to understand further if any risks are associated with pursuing it and how those can be addressed. Were policy failures still to occur, however, note that these are also instances of capability learning, potentially allowing countries to succeed a second or third time (Stiglitz, 2017). Nonetheless, countries should be cautious as other risks with industrial strategy remain – they can create economic inefficiencies, lock-in effects, and trade disputes (Lewis, 2021; Meckling et al., 2017; Meckling, 2021), or misalign incentives in combination with other policies (Fankhauser et al., 2010), all of which can lead to a slower or costlier green transition.

Finally, this paper has also advanced the methodology of the principle of relatedness (Hidalgo et al., 2018). We show that this principle holds in an industrial strategy context too, opening up further research possibilities. Methodologically, we show that all three network projections of our tri-partite approach carry different and complementary information. This contrasts with most previous studies, which tend to focus on one relatedness network, even though their bipartite network approach often implies that two projected relatedness networks exist (Hidalgo, 2009; Nomaler and Verspagen, 2022), both of which can carry different information (Everett and Borgatti, 2013). Future research can look into how the different relatedness networks of the same bi/tripartite network relate to one another and what that means for our understanding of the principle of relatedness.

In this work, we have shown the existence and structure of path dependence in different dimensions of green industrial strategy, but our methods and results are generic and can be used for other datasets and policy domains. Our results can be a starting point to understand better the history and future trajectory of green industrial strategy, and it can give policymakers an understanding of their specific context in relation to others. Our results and recent literature on the principle of relatedness also suggest that this path dependence is a more general phenomenon that may be present in other fields of policy and beyond. We leave these questions for future research.

Materials and methods

Data

Industrial strategy data

Our industrial strategy data is from Global Trade Alert (GTA) (Evenett, 2009). GTA covers “credible announcement of a meaningful and unilateral change in the relative treatment of foreign versus domestic commercial interests” (Evenett and Fritz, 2020). It includes announcements made after November 2008 by any jurisdiction and is continuously updated. GTA is one of the most extensive datasets of industrial strategy (Hoekman, 2020). However, it excludes policies that the WTO deems to have an ‘uncontested higher motive’, allowing countries to add restrictions on goods that are, for example, environmentally damaging (Jensen, 2023). GTA data has been used in several publications related to industrial strategy and trade policy, including for policies and trade during covid (Thrasher et al., 2023), green stimulus (Lewis, 2021), and solar PV protectionism (Jensen, 2023).

Industrial strategy or policy is not always well defined. Juhász et al. (2022) note that any definition of industrial strategy should encompass two lenses on state intervention: the neoclassical idea of correcting market failures and the developmental idea of achieving a more desirable economic structure. The latter is done through discovering and supporting competitiveness (Rodrik, 2004). In that vein, Altenburg and Rodrik (2017) note that ‘industrial policy’ often goes beyond *policies on industries* and offers alternative phrases such as *structural transformation policies* or *productive development policies*. In this study, we use the term ‘industrial strategy’ for the broader phenomenon and ‘industrial policy’ when discussing specific policies or policy adoptions.

The industrial strategy data from GTA includes 42,548 unique State Act IDs, 51,761 unique Intervention IDs, and 84,460 policies, of which 37,440 unique Intervention IDs, and 64,421 policies ‘almost certainly’ or ‘likely’ discriminate against foreign commercial interests. Multiple policies can be associated with the same state act and intervention, but will concern different policy instruments, affected products, and/or time frames. We use the data up to 1 Jan 2022. While more recent data is available, some policies are only announced – and thus added to the data – some time after they were implemented. To avoid any artifacts because of this, we decided to keep only policies that were implemented before 1 Jan 2022.

Most policies in the dataset include a list of the Harmonized System (HS) codes (at the 2012 vintage) of the products that it affects. These are either taken from the official source of policy documentation by the GTA team or imputed by them based on the policy text (Evenett and Fritz, 2020). We are interested in policies that affect specific products that can be mapped to the HS 1992 vintage (HS92) codes: 23,311 State Act IDs, 25,094 Intervention IDs, and 37,303 policies include that data. Other policies can be generic, affecting a country's entire economy, or incomplete. We say a policy is *active* between the inception and removal date. Policies without a removal date are still active by the end of the study period. We restructure the data so that each policy in our dataset consists of one implementing country, one policy instrument, an active time frame, and a set of affected HS92 products. To create the industrial strategy networks, we break these down into smaller policy tuples of one country, one product, and one instrument.

A *new* policy in our study is the first time (since the start of our data in late 2008) that a country targets a particular product with a specific policy instrument.

Our data tracks the number of policies – also called policy 'density' – but not the total financial cost or economic impact in monetary terms (Schaffrin et al., 2015). This is an important limitation. In a climate policy context, however, policy density has been used to indicate climate change action ambition (Schaub et al., 2022) and faster greenhouse gas emission reduction (Eskander and Fankhauser, 2020).

Green value chains

The data on green products used in this study comes from Rosenow and Mealy (2024). Through literature search and expert elicitation, they identified 240 products in the HS92 classification of products that are part of the value chains of solar PV, wind turbines, and electric vehicles (EVs); for EVs, we use their *narrow* classification, which excludes vehicle parts that are also required for internal combustion engine (ICE) cars. Rosenow and Mealy (2024) also classified the products as raw materials, processed materials, sub-components, or end products.

Green industrial policies in this study are policies in GTA that affect at least one HS92 product in the narrow green product dataset of Rosenow and Mealy (2024).

Relationship to other definitions and datasets of green industrial strategy

Green industrial strategy is a subset of industrial strategy that Hallegatte et al. (2013) define as “sector-targeted policies that affect the economic production structure with the aim of generating environmental benefits”. Karp and Stevenson (2012) keep their definition more limited to climate change when they talk of “government attempts to hasten the development of low-carbon alternatives to fossil fuels”.

Taking a broader view, Altenburg and Rodrik (2017) note that green industrial strategy attempts to tackle the “dual challenge of creating wealth and greening economies”. They list six distinct features of green industrial strategy over other forms, including the existence of metrics to distinguish good from bad technologies, the urgency yet uncertainty due to long time horizons, and a global – rather than local – commons problem. Harrison et al. (2017) see two applications of green industrial strategy: one that promotes green technologies and another that incentivizes non-green industries to produce in a cleaner way.

Our data differs in scope from other (green) industrial strategy datasets and definitions. Our data is a subset of the global trade alert (GTA), which collects “credible announcement[s] of meaningful and unilateral change in the relative treatment of foreign versus domestic commercial interests" (Evenett and Fritz, 2020; Evenett, 2009). It is, therefore, relatively broad in the policy scope. For example, Juhász et al. (2022) also use GTA data but restrict it to policies that have an explicit industrial strategy motivation. Hallegatte et al. (2013) also include the 'aim' of the policy as an important characteristic of green industrial strategy.

On the other hand, our definition is more restrictive regarding non-neutrality. GTA only includes policies that are non-neutral with regard to domestic and foreign producers. This means that policies that affect a product's demand (such as household subsidies for rooftop solar) are excluded, as long as there are no restrictions on where the product is produced. This is a restriction that is often but not always made to define industrial strategy (Hallegatte et al., 2013).

Finally, our definition has a specific green focus distinct from other approaches. We focus on policies targeting the manufacturing of renewable energy products and their value chain. Our definition of 'green' is thus more in line with that of Karp and Stevenson (2012) regarding low-carbon alternatives to fossil fuel, as well as the first part of Harrison et al. (2017)'s definition on promoting green technologies, but it excludes their second part on policies that aim to decarbonize industrial processes more generally. Conversely, our scope includes products that are key for the renewable energy value chain but may not seem green on first inspection, such as steel ball bearings, which are key components of wind turbine rotor connections.

Methods

Industrial policies, value chains, and green overlap

An industrial policy i is defined as the 4-tuple $\mathcal{I}_i = \{c_i, P_i, T_i, \tau_i\}$ with an implementing country c_i, set of products $P_i \subseteq \mathcal{P}$ that it affects, where $\mathcal{P}$ is the set of all products, time period $T_i = \{t_{i0}, t_{i1}\}$ when it is active, and policy instrument τ_i.

The value chain set $V_x \subseteq \mathcal{P}$ of technology x – e.g., *solar PV* – is the set of products that are part of the value chain of x. $V_{\text{green}} = V_{\text{wind energy}} \cup V_{\text{solar PV}} \cup$

$V_{\text{EV batteries}}$ is the set of all green products in this study.

The green overlap $r_{i,\text{green}}$ between policy i and the green value chain is calculated as the Jaccard index between the products in the green value chain and those targeted by policy i:

$$r_{i,\text{green}} = \frac{P_i \cap V_{\text{green}}}{P_i \cup V_{\text{green}}}. \tag{4}$$

Fig. 9 shows four examples of the green overlap for different policy and green value chain product sets.

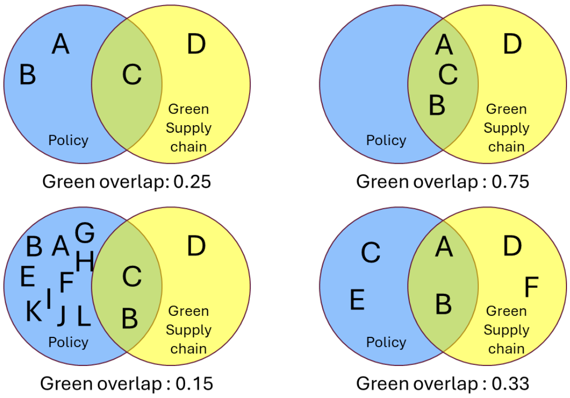


Figure 9: **Green overlap examples.** Letters represent products, and the Venn diagram visualizes the overlap in products between policies and green value chains. The green overlap is the Jaccard index of the product sets.

Industrial strategy networks

To create the networks in Figs. 4–7, we follow the network projection method from Hidalgo et al. (2007). For the industrial strategy instrument network, we calculate the relatedness between two instruments based on their co-occurrence in product-country pairs. Equivalently, this represents the empirical conditional probability that one of the instruments was introduced on a product-country pair, given that the other was as well.

Let $M_{icp} = 1$ if country c has introduced a policy with instrument i on product p over the included period. Thus, $M_{icp} = 1$ iff $\exists\, \mathcal{I}_j \in \mathcal{I}$ such that $c = c_j, p \in P_j, i = \pi_j$. The three dimensions of M allow us to define three measures of relatedness, which form the edge weights on the three networks.

In the industrial strategy instrument network, the edge weight is the *instrument relatedness* ϕ_{ij}^{instr} between policy instruments i and j:

$$\phi_{ij}^{\text{instr}} = \min\left(\frac{\sum_{cp} M_{icp} M_{jcp}}{\sum_{cp} M_{icp}}, \frac{\sum_{cp} M_{icp} M_{jcp}}{\sum_{cp} M_{jcp}}\right), \tag{5}$$

where the minimum operator ensures that the network is symmetric and that the relatedness between rare and ubiquitous instruments is low.

Symmetrically, the edge weight in the product network between products p and q is the *product relatedness* ϕ_{pq}^{prod}:

$$\phi_{pq}^{\text{prod}} = \min\left(\frac{\sum_{ic} M_{icp} M_{icq}}{\sum_{ic} M_{icp}}, \frac{\sum_{ic} M_{icp} M_{icq}}{\sum_{ic} M_{icq}}\right), \tag{6}$$

and the edge weight in the country network between countries c and d is the *country relatedness* ϕ_{cd}^{ctry}:

$$\phi_{cd}^{\text{ctry}} = \min\left(\frac{\sum_{ip} M_{icp} M_{idp}}{\sum_{ip} M_{icp}}, \frac{\sum_{ip} M_{icp} M_{idp}}{\sum_{ip} M_{idp}}\right). \tag{7}$$

Community detection

We use the Louvain community detection algorithm (Blondel et al., 2008) to group the 42 instruments into five clusters in Fig. 4. See Supplementary Materials Section A for more information.

Network visualizations

The network visualizations use the entire 2008–2022 dataset, limited to the 42 policy instruments that were implemented in at least five different countries.

The full networks are dense and contain many edges with a low relatedness score ϕ. To minimize noise, we backbone the network following the method of Hidalgo et al. (2007). The backbone instrument network and the backbone country network contain the edges of the full network's minimum spanning tree plus all edges with a relatedness greater than a half standard deviation above the mean. The product network is much larger and denser. The product backbone network, therefore, only contains the edges of its full network's minimum spanning tree plus all edges with a relatedness greater than two standard deviations above the mean.

Policy alignment

Using the networks, we can define three metrics of policy alignment, which quantify how 'close' a new policy is on the network to the portfolio of previously implemented policies.

The industrial strategy *instrument alignment* $\omega^{\text{instr}}_{cp,i}$ is the fraction of policy instruments 'surrounding' instrument i on the instrument network that has already been introduced on product p in country c. This closely follows earlier economic geography literature on network spreading, particularly Hidalgo et al. (2007)'s definition of *density*, a metric of 'closeness' between a country's export basket and a product. Here, we define $\omega^{\text{instr}}_{cp,i}$ as

$$\omega^{\text{instr}}_{cp,i} = \frac{\sum_j M_{jcp}\phi^{\text{instr}}_{ij}}{\sum_j \phi^{\text{instr}}_{ij}}. \tag{8}$$

Higher values of instrument alignment $\omega^{\text{instr}}_{cp,i}$ indicate that country c has introduced 'nearby' instruments on product p but not yet instrument i. Instrument alignment is undefined for instruments already adopted on the particular country-product pair.

The *product alignment* $\omega^{\text{prod}}_{ic,p}$ is, symmetrically, the fraction of products 'surrounding' product p that have already been subjected to policy instrument i in country c:

$$\omega^{\text{prod}}_{ic,p} = \frac{\sum_q M_{icq}\phi^{\text{prod}}_{pq}}{\sum_q \phi^{\text{prod}}_{pq}}; \tag{9}$$

and the *country alignment* $\omega^{\text{ctry}}_{ip,c}$ follows analogously as

$$\omega^{\text{ctry}}_{ip,c} = \frac{\sum_d M_{idp}\phi^{\text{ctry}}_{cd}}{\sum_d \phi^{\text{ctry}}_{cd}}. \tag{10}$$

Counterfactual analysis

The counterfactual analysis allows us to show the potential effect size of the regression results. We calculate the coefficients and fixed effects of the probit model of Eq. (1) with instrument alignment only (Model (1) in Table 2). Then, we calculate the factor f_{pci}, which is the ratio of the full model output over the model output with instrument alignment set to zero:

$$f_{pci} = \frac{\Phi\left(\widehat{\beta}\omega^{instr}_{pci} + \widehat{\gamma}_c + \widehat{\delta}_p + \widehat{\eta}_i\right)}{\Phi\left(\widehat{\gamma}_c + \widehat{\delta}_p + \widehat{\eta}_i\right)}. \tag{11}$$

Factor f_{pci} calculates how much more likely the new policy combination of product p - country c - instrument i becomes given its level of instrument alignment, compared to the counterfactual situation of zero alignment – i.e., as if no related policy instruments had been introduced before.

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Materials contained in Supplementary Materials

Section A. Community detection in the industrial strategy instrument network

Section B. Product categories

Section C. Extended regression tables

Figure S1. Community detection using the Louvain algorithm.

Table S1. Product categories and their corresponding HS two-digit starting codes.

Table S2. Policy adoption regression with all product data.

Table S3. Policy adoption regression with a linear probability model.

Table S4. Policy adoption regression with all product data and a linear probability model.

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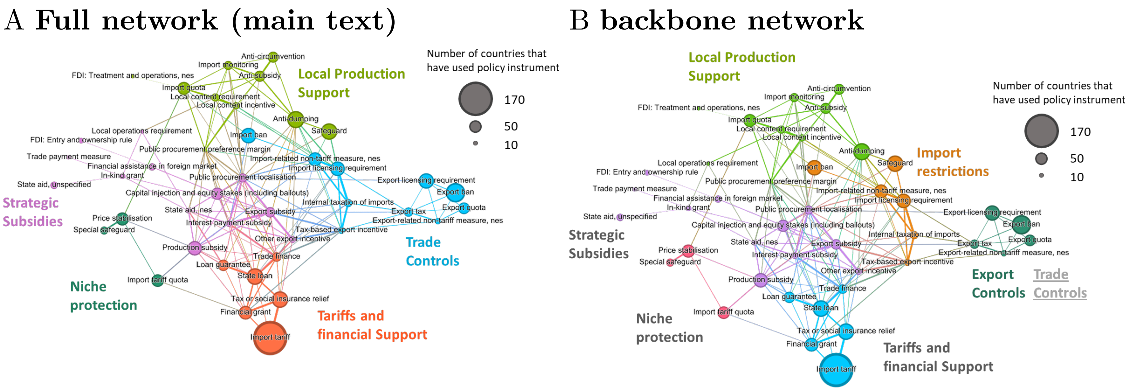
Reference (Blondel et al., 2008)

Supplementary Materials

Contents

A Community detection in the industrial strategy instrument network

In Fig. 4 in the main text, we color the nodes by the five network communities found by the Louvain algorithm (Blondel et al., 2008) on the full network (i.e., with all edges and not backboned). This network is reproduced here in Fig. S1A. Conversely, the algorithm finds six communities in the backbone network (Fig. S1B). The overlap with the five communities found on the full network is substantial, but there are some differences. One Local product support instrument and five Trade control instruments form a new community. We have named this community *Import restrictions* and renamed the remaining *Trade controls* to *Export controls*, which matches the remaining instruments closer. Due to their similarities, we decided to use the full network communities in the main text.



A **Full network (main text)**

B **backbone network**

Figure S1: **Community detection using the Louvain algorithm.**

B Product categories

Table S1 lists the product categories used in the main text and their corresponding HS codes.

HS starting codes	Product category
01–05	Animals & animal products
06–15	Vegetable products
16–24	Foodstuff
25–27	Mineral products
28–38	Chemicals & allied products
39–40	Plastics & rubbers
41–43	Leather & hides
44–49	Wood & wood products
50–63	Textiles
64–67	Footwear & headgear
68–71	Stone & glass
72–83	Metals
84–85	Machinery & electrical products
86–89	Transportation products
90–97	Miscellaneous products

Table S1: **Product categories and their corresponding HS two-digit starting codes.**

C Extended regression tables

C.1 All products

Dep. Var.:						New policy adoption						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.040^{***}			0.033^{***}	0.009^{***}			0.006^{***}	0.041^{***}			0.042^{***}
	(0.006)			(0.006)	(0.001)			(0.001)	(0.003)			(0.003)
ω^{prod}		0.034^{***}		0.030^{***}		0.075^{***}		-0.001		0.026^{*}		-0.045^{**}
		(0.007)		(0.008)		(0.008)		(0.008)		(0.013)		(0.015)
ω^{ctry}			0.026^{*}	0.027^{*}			0.059^{***}	0.059^{***}			0.036^{***}	0.040^{***}
			(0.012)	(0.013)			(0.001)	(0.002)			(0.003)	(0.004)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Obs.	41,052,231	41,052,231	41,052,231	41,052,231	1,484,110	1,484,110	1,484,110	1,484,110	841,020	841,020	841,020	841,020
Pseudo R^2	0.448	0.450	0.446	0.455	0.560	0.560	0.563	0.563	0.473	0.471	0.472	0.474

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S2: **Policy adoption regression with all product data**. Effect of policy alignment on the adoption of new industrial policies using a probit model. Standardized regression coefficients.

C.2 Linear probability model

Dep. Var.:						New policy adoption						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.008^{***}			0.004^{***}	0.004^{***}			0.003^{***}	0.004^{***}			0.003^{***}
	(0.0009)			(0.001)	(0.0002)			(0.0002)	(0.0003)			(0.0003)
ω^{prod}		0.007^{***}		0.004^{***}		0.041^{***}		0.033^{***}		0.041^{***}		0.034^{***}
		(0.0010)		(0.0009)		(0.002)		(0.002)		(0.003)		(0.003)
ω^{ctry}			0.009^{***}	0.007^{**}			0.006^{***}	0.004^{***}			0.004^{***}	0.002^{***}
			(0.002)	(0.002)			(0.0003)	(0.0003)			(0.0004)	(0.0004)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Obs.	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367	2,436,367
R^2	0.048	0.049	0.053	0.065	0.310	0.312	0.311	0.314	0.561	0.562	0.561	0.563
Within R^2	0.014	0.016	0.020	0.031	0.002	0.005	0.003	0.008	0.002	0.003	0.001	0.006

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S3: **Policy adoption regression with a linear probability model**. Effect of policy alignment on the adoption of new green industrial policies using a linear probability model. Standardized regression coefficients.

Dep. Var.:						New policy adoption						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.005^{***}			0.002^{*}	0.002^{***}			0.002^{***}	0.003^{***}			0.003^{***}
	(0.0006)			(0.0008)	(5.32E-5)			(5.28E-5)	(0.0001)			(0.0001)
ω^{prod}		0.008^{***}		0.005^{***}		0.035^{***}		0.029^{***}		0.029^{***}		0.022^{***}
		(0.001)		(0.001)		(0.0005)		(0.0005)		(0.001)		(0.001)
ω^{ctry}			0.009^{***}	0.007^{**}			0.005^{***}	0.003^{***}			0.005^{***}	0.003^{***}
			(0.002)	(0.002)			(7.29E-5)	(7.48E-5)			(0.0002)	(0.0002)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Obs.	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872	48,396,872
R^2	0.040	0.054	0.059	0.072	0.338	0.341	0.340	0.343	0.534	0.535	0.535	0.537
Within R^2	0.009	0.025	0.029	0.043	0.001	0.006	0.004	0.009	0.003	0.004	0.003	0.007

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S4: **Policy adoption regression with all product data and a linear probability model**. Effect of policy alignment on the adoption of new industrial policies using a linear probability model. Standardized regression coefficients.

C.3 Cutoff year sensitivity

The main text uses the cutoff year of 2016. Here, we replicate Table 2 from the main text for 2013 and 2019.

C.3.1 Cutoff year 2013

Dep. Var.:						New policy adoption						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.005			0.004	0.013^{***}			0.004	0.031^{***}			0.032^{***}
	(0.006)			(0.007)	(0.003)			(0.003)	(0.008)			(0.009)
ω^{prod}		0.011		0.013		0.112^{***}		0.068^{***}		$0.041^{\cdot}$		0.003
		(0.012)		(0.011)		(0.018)		(0.018)		(0.024)		(0.024)
ω^{ctry}			-0.005	-0.010			0.049^{***}	0.046^{***}			0.013^{***}	0.013^{***}
			(0.008)	(0.009)			(0.005)	(0.005)			(0.004)	(0.004)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Observations	1,444,014	1,444,014	1,444,014	1,444,014	133,380	133,380	133,380	133,380	52,743	52,743	52,743	52,743
Pseudo R^2	0.541	0.542	0.541	0.542	0.634	0.635	0.637	0.638	0.419	0.418	0.419	0.420

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S5: **Policy adoption regression with cutoff year 2013**. Effect of policy alignment on the adoption of new green industrial policies using a probit model. Cutoff year 2013. Standardized regression coefficients.

C.3.2 Cutoff year 2019

Dep. Var.:	New policy adoption											
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ω^{instr}	0.068***			0.064***	0.092***			0.078***	0.068***			0.069***
	(0.009)			(0.008)	(0.011)			(0.011)	(0.017)			(0.017)
ω^{prod}		0.021*		0.010		0.405***		0.206**		0.344**		0.166
		(0.009)		(0.010)		(0.067)		(0.068)		(0.110)		(0.112)
ω^{ctry}			0.012	0.009			0.098***	0.085***			0.065***	0.060**
			(0.014)	(0.014)			(0.014)	(0.014)			(0.017)	(0.018)
Fixed-effects												
C-P(2d)-I									Yes	Yes	Yes	Yes
C-P					Yes	Yes	Yes	Yes				
C-I					Yes	Yes	Yes	Yes				
P	Yes	Yes	Yes	Yes					Yes	Yes	Yes	Yes
C	Yes	Yes	Yes	Yes								
I	Yes	Yes	Yes	Yes								
Fit statistics												
Obs.	988,631	988,631	988,631	988,631	20,910	20,910	20,910	20,910	20,019	20,019	20,019	20,019
Pseudo R^2	0.374	0.365	0.363	0.375	0.439	0.436	0.442	0.447	0.447	0.445	0.447	0.450

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S6: **Policy adoption regression with cutoff year 2019**. Effect of policy alignment on the adoption of new green industrial policies using a probit model. Cutoff year 2019. Standardized regression coefficients.

3 Employment dynamics in a rapid decarbonization of the US power sector

Joris Bücker[1,2,8,*], R. Maria del Rio-Chanona[3,4,5], Anton Pichler[6,5],
Matthew C. Ives[1,2], and J. Doyne Farmer[1,2,7]

[1] *Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK*
[2] *Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK*
[3] *University College London, University of London*
[4] *Bennett Institute for Public Policy, University of Cambridge, Cambridge, UK*
[5] *Complexity Science Hub, Vienna, Austria*
[6] *Vienna University of Economics and Business, Vienna, Austria*
[7] *Santa Fe Institute, Santa Fe, NM, US*
[*] *Correspondence: joris.bucker@seh.ox.ac.uk*
[8] *Lead contact*

Summary

We analyze the employment dynamics of a rapid decarbonization of the US power sector, reducing emissions by 95% before 2035. We couple an input-output model with an occupational mobility network and identify three labor market phases: 'scale-up', 'scale-down', and a long-term, low-carbon, 'steady state'. During the scale-up (2023–2034), for every job lost in an industry, twelve new jobs are created elsewhere. However, few occupations see sustained growth throughout the transition. We predict that skill mismatches will create frictions during the transition, especially in the scale-down phase. Compared to the size and fluctuations of the US labor market, the impact of this transition is modest, particularly if the US increases exports of clean energy technologies to counteract the domestic scale-down phase. However, without proper planning, rapidly growing industries will struggle to find skilled labor during the scale-up phase, while displaced workers might struggle to find jobs during the scale-down phase.

Introduction

An immediate and accelerated decarbonization of the global economy is required to limit global warming to below 2°C above pre-industrial levels (IPCC, 2018; Armstrong McKay et al., 2022). Since the majority of greenhouse gas emissions (more than 75%) are energy related, the rapid expansion of renewables and the phase-out of fossil fuels has become a key focus in near-term mitigation strategies (IEA, 2021). While a fast transition to a net zero energy system could end up being economically beneficial by itself (Way et al., 2022; Creutzig et al., 2023), it will still have profound impacts on countries' economies, including their labor markets.

The net-zero energy transition will create and destroy jobs. On the one hand, the transition will lead to a downscaling or removal of fossil fuel energy generation with an associated displacement of workers. Past experiences of long-term depressions from shrinking industries and mine closures in North England, the US Appalachians, and the German Ruhr areas underscore the importance of managing such transitions and finding ways to alleviate the negative impacts of stranded labor on displaced workers and communities (Oei et al., 2020; Gore and Hollywood, 2009; Olson-Hazboun, 2018; Beatty et al., 2007; Carley and Konisky, 2020).

On the other hand, a net-zero transition will create a demand for many new workers to build and manage the new clean energy infrastructure, leading to the possibility of skill shortages and unfilled vacancies. This will be exacerbated if the overall labor market is tight[1], as it currently is in many places in Europe and North America (Domash and Summers, 2022). A shortage of workers with the right skills could slow down the energy transition.

Previous literature is broadly aligned in concluding that there will be a net gain of jobs in the US during a clean energy transition. For example, Jacobson et al. (2015) find almost 2 million net jobs created in the US (6 million gained, 4 million

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[1] The labor market is tight if the ratio between unemployment and vacancies is significantly larger than one.

lost), while the ILO (2018) finds a 0.45% economy-wide net increase in employment for the Americas as a whole, representing around 700,000 jobs[2] for the US if we assume it follows the regional average. Mayfield et al. (2023) estimate that the fraction of the US workforce in the energy supply chain will grow from 1.5% in 2020 to 2.5–5% in 2050, representing approximately a 1.5–6 million increase in workers. Ram et al. (2022) find a roughly 4 million net increase in energy-related jobs between 2020 and 2050 for the US in a 100% renewable energy scenario. Xie et al. (2023) find an increase of 439,000 jobs by the 2040s if the power sector reaches net zero emissions by 2035. Other studies finding job growth include Dell'Anna (2021), Lehr et al. (2008) and Černý et al. (2022). Only a few studies find a negative impact on job creation; for an overview, see, e.g., Stavropoulos and Burger (2020).

Most of these studies only focus on aggregate job numbers in the initial transition phase and do not address the heterogeneity of impacts across workers and over time. Workers' occupations, skills, experience, geographic location, available alternative employment options, and perceived socio-economic status can affect their employment prospects (Hollywood, 2002; Schmutte, 2014; Diodato and Weterings, 2015; Nedelkoska et al., 2018; Neffke et al., 2024). Workers are more likely to transition to jobs in industries and occupations related to their previous job (Mealy et al., 2018; Neffke and Henning, 2013; Hausmann and Neffke, 2019). This can have significant implications for employment. When new vacancies are opened in occupations that are very unrelated to occupations where workers lose their jobs, a skill mismatch is created, rendering it challenging for displaced workers to find new roles as their usual job alternatives are not available (Del Rio-Chanona et al., 2021).

The net-zero transition has the potential to generate skill mismatches, which can evolve over time. To assess the employment implications of the net-zero transition, it is important to consider the heterogeneous effects across all occupations and over time. Traditional global integrated assessment models rarely analyze the evolving

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[2] In June 2023, about 161 million people were employed in the US (BLS, 2023).

labor structure or categorize households by occupation, lacking information on employment shifts linked to specific mitigation scenarios (Rao et al., 2017). Although some macroeconomic models have begun to explore labor market impacts at a detailed level and consider different skills and occupations (ILO, 2018; Mayfield et al., 2023), most of these studies overlook potential skill mismatches that result from correlated displacement shocks across occupations and over time.

The skill mismatch literature often builds on network models. Three studies stand out in examining potential skill mismatches resulting from the net-zero transition: Lankhuizen et al. (2023) apply an industry and geography mobility model to the Netherlands, and Berryman et al. (2023) use a computable general equilibrium model linked with an occupational mobility model for Brazil. These studies identify potential skill mismatches that could lead to higher rates of unemployment or unfilled vacancies. Additionally, Xie et al. (2023) look at the distributional effects for workers of a US power sector decarbonization, disaggregated by skill level and gender across states.

To understand the potential for skill mismatch frictions in the net-zero transition, previous work classifies occupations into 'green' and 'brown' categories depending on their skills, industry employment, or future outlook in a decarbonizing economy, sometimes with sub-classifications for green jobs. For example, O*NET classifies occupations as 'Green New & Emerging' if they are likely to see a demand increase when shifting to a 'greener' economy (Dierdorff et al., 2009). Vona et al. (2018) analyze the characteristics of green and brown occupations in a labor market network. The labor transition is complicated by the fact that green jobs tend to require higher skills, are more often located in urban areas and are less prone to automation than brown jobs (Bergant et al., 2022; Bowen et al., 2018; Saussay et al., 2022). Nevertheless, more transitions from brown to green jobs can be expected as the availability of green jobs increases (Curtis et al., 2023).

In this study, we argue that temporal effects play a crucial role in the net-zero transition. The classification of occupations as 'green' or 'brown' overlooks the fact that some roles may be crucial for only part of the transition. While some macroeconomic models can deal with temporal changes in demand, their focus is often restricted to the initial scale-up phase. This approach neglects the later stages when generation capacity has shifted to renewables, and worker demand may decline, particularly in construction and manufacturing. The narrow focus on job growth in the initial transition phase can lead to misunderstandings of the complexities involved in the full trajectory to a net-zero economy.

We develop a novel framework for analyzing occupation-specific skill mismatches as they evolve during the clean energy transition. In our framework, if the demand for occupations with similar skills rises in tandem, it becomes relatively harder for employers to fill vacancies, and, if it falls in tandem, it becomes harder for workers to find new jobs. Our goal is to alert policymakers to these frictions, so that they can make targeted interventions to mitigate skill mismatch frictions.

We follow a four-step procedure (see Experimental Procedures, Fig. 7). First, we translate the different cost components (capital expenditure, operational expenditure and fuel cost) of power sector decarbonization scenarios into annual demand shocks and intermediate consumption changes.

Second, we use a simple demand-driven input-output (IO) model to estimate direct and upstream industry output changes as a consequence of the changing energy mix. To do this, we disaggregate the IO data to include ten different electricity technologies. Our model is dynamic: in each year of the analysis, we update the links in the IO network in tandem with the energy mix (e.g., when the coal power share of electricity production is reduced in favor of wind energy, industries and households switch part of their demand from coal power to wind).

Third, we calculate annual labor demand profiles for all occupations and industries, assuming a fixed employment and occupation breakdown per constant-dollar output – this also means that wages are kept constant in real terms. This assumption allows for any energy technology cost reductions to be translated into decreased labor demand for the same product, accounting for automation and innovation through the electricity supply chain.

Finally, by linking occupational demand trajectories to an occupational mobility network, we quantify potential skill mismatch frictions. All such 'skill mismatch' or labor market frictions identified by this study relate to the difficulty of changing one's occupation at different stages of the clean energy transition. To test the robustness of our results, we engage in extensive sensitivity analysis of key assumptions and data sources (see Section D.6 of the SM).

We apply our method to the United States using the National Renewable Energy Laboratory (NREL)'s standard scenarios, focusing on their fast transition scenario that reaches 95% decarbonization in the power sector by 2035 (Cole et al., 2021). We are interested in this scenario partly because accelerated climate action is required to meet the US's Paris pledge to keep global warming well below 2 °C. All the results in the main text concern the implications of the *95% by 2035* scenario relative to NREL's *no-new-policy* scenario, which we take as the *reference* scenario.

Recently announced policies, such as those included in the Inflation Reduction Act (IRA), also make a fast transition in the power sector more likely. The current US President Biden's stated goal is to deliver 100% clean electricity by 2035 (The White House, 2023). The IRA moves the US much closer to that trajectory, although Bistline et al. (2023) show that IRA-compliant power sector scenarios could still fall short of this target. A fast decarbonization might also be accelerated further by economic forces if it becomes financially beneficial (Way et al., 2022; Creutzig et al., 2023).

NREL is a US Department of Energy sponsored research center that produces scenarios that are closely examined by US policymakers, with high credibility in the research community. NREL's fast transition scenario also covers both the transition phase and a subsequent low carbon power system phase of an energy sector that is decarbonized by 2050, enabling us to assess the full temporal implications of the transition.

NREL does not make assumptions about whether clean technologies are imported or produced domestically, so we need to specify that ourselves. However, it is important to bear in mind that a substantial fraction of the demand for labor from the clean energy transition is domestic, independent of imports and exports. This is because almost all of the operational expenses are for domestic labor, and many categories of capital expenses are for domestic industries such as construction. Thus, while what happens in terms of imports and exports is important, we find our basic conclusions hold across a range of plausible import and export scenarios, as shown in Figs. S18–S21 in Section D.6 of the SM. Our main assumptions represent a form of "business as usual": keeping the *relative share* of import of capital goods constant at 2018 levels, while keeping exports fixed in *absolute* terms. The logic for our approach and a description of the alternate scenarios, and how they affect the results, is given in the section titled "Robustness of results".

Our model works with national-level data and thus neglects sub-national differences. The total flux of workers that the NREL scenario causes in our model is small, especially for large industries such as construction and manufacturing that are engaged in many activities beyond renewable energy. But local impact can be more problematic. Green jobs are likely to arise in different locations than fossil fuel jobs (Lim et al., 2023), which can amplify skill mismatches. Vice versa, locations without any green or brown energy-related jobs may not be affected at all. We discuss how our analysis can be extended to include geography in the Supplemental Experimental Procedures Section B.1.

Since we are concerned with the labor impacts of decarbonizing the power sector and its upstream industries, an IO network provides a straightforward way to convert the scenario's annual energy system spending into changes in direct and upstream labor demand. This should not be interpreted as a macroeconomic model, as it lacks mechanisms such as prices and substitutability; any additional energy demand effects caused by electrification or changes to the costs of energy services are assumed to have already been included in the NREL energy scenarios that we apply.

We make three contributions to the wider debate on the labor market impact of the green transition. First, we show that the aggregate demand for jobs does not follow a linear pattern, but rather three distinct phases – scale-up, scale-down, and the low carbon power system. Second, we challenge the commonly used green vs brown jobs dichotomy of occupations, providing a more accurate and meaningful list of demand trajectory typologies for occupations – temporary growth, consistent growth, consistent decline, and late growth. Third, we use methods from network science to quantify the frictions faced both by employers seeking qualified labor and workers looking for jobs in each phase of the transition.

While it is beyond the scope of this work, the extent and timing of further electrification and prospective efficiency drives will be important factors. To focus specifically on the labor impacts of the low carbon transition, all of our results are shown as relative to a second NREL *no-new-policy reference* scenario. We apply our method to the US transition, but, with sufficient data, this approach could be applied to virtually any modeled energy-economy transition scenario for any country or region.

The remainder of this paper is organized as follows. In the section "Temporal heterogeneity in labor demand during the transition", we present the transition scenarios and estimations of labor demand dynamics. This is followed by "Temporal typology of occupational demand change", where we introduce our suggested classification of occupations according to the demand dynamics. In "Skills shortages and stranded labor", we use network tools to identify potential skill mismatches and frictions. We discuss the results of several robustness checks in the section "Robustness of Results". We conclude with a discussion of this paper's contributions and implications. Our methodological approach, based on coupling power transition scenarios with a dynamic input-output model to assess labor demand and occupational mobility, is detailed in “Experimental procedures”.

Temporal heterogeneity in labor demand during the transition

The two NREL scenarios we use are shown in Fig. 1. The left panels display the capacity and generation profile of the *reference* scenario that we use, which assumes no new carbon reduction policies beyond those in place as of June 2021 (without, e.g., the more recent Inflation Reduction Act). The right panels depict the fast transition scenario, where the model is required to reach a 95% decarbonized system from 2035 onward. Both models are the result of a cost-optimized energy model with fixed and inelastic electricity demand. The increase in renewables in the *reference* scenario, for example, shows the cost-effectiveness of including renewables with policies as of June 2021. For more details on the modeling assumptions used in the NREL scenarios, see Cole et al. (2021). The corresponding emission pathways are shown in the Supplemental Experimental Procedures Fig. S1. The *95% by 2035* scenario results in slightly higher total generation because of higher losses during transmission and storage, and energy used for carbon capture. Note that we model natural gas with carbon capture technology as a separate variety included in the natural gas part of our study (see SM Table S1 in SM Section C.1).

The fast transition scenario we consider here is an interesting study case, but it should be pointed out that other low-carbon energy mixes are feasible, possibly involving very different sets of technologies (e.g., see Pickering et al. (2022); Bistline et al. (2023)). Different technology choices would lead to different labor market impacts. Thus, the results presented should not be understood as covering the whole spectrum of labor market impacts of the power sector transition but, rather, model the potential impacts of specific future scenarios.

In SM Section D.1 and accompanying SM Fig. S7, we show how the scenarios translate to operating expenses (opex) and capital expenses (capex), taking replacement and newly built capacity into account. In the *95% by 2035* scenario, we find a large increase in investment in renewable technologies (solar, wind, batteries) and the transmission and distribution network until 2035 and a decline afterwards. On the opex side, renewable technologies require a larger share of total cost over time in the *95% by 2035* scenario, while the main change in the *reference* scenario is a switch from coal to natural gas opex. As explained further in the Experimental procedures section, we use an input-output model to estimate the direct and indirect – supply chain – effects on worker demand.

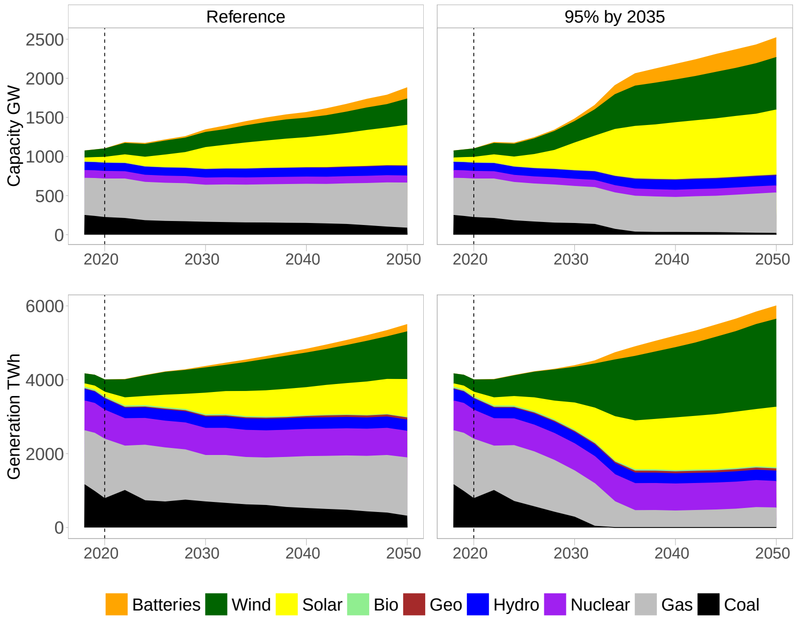

Figure 1: **The US power sector scenarios we use in this study.** The upper panels show the capacities in GW, and the lower panels show the electricity generation in TWh in yearly resolution. On the left, we show NREL's *no-new-policy reference* scenario that we use as the counterfactual and on the right NREL's fast *95% by 2035* scenario. Source: NREL (Cole et al., 2021), with technological categories aggregated according to SM Table S1: Gas electricity also includes gas with carbon capture and storage (CCS) technology. Up to 2020, the figures show historical data from the Electric Power Annual 2020 (EIA, 2022).

Transition scenario and labor market impact

In Fig. 2, we present our model's estimates of the labor demand relative to the *reference* scenario for industries and occupations between 2020 and 2050. For visualization purposes, the labels indicate 2-digit NAICS industry classification codes (20 industries) and 22 high-level occupational categories, but this is an aggregation of results using a more detailed classification of 82 industries and 539 occupations. These industries and occupations represent all nonfarm US firms and workers – with the exception of the US government defense sector. See Supplemental Experimental Procedures Section E for the full list of industries and occupations. When we refer to 'jobs' gained (lost) or worker demand that increased (decreased) in this study, we refer to the net increase (decrease) in demand within industries or occupations relative to the *reference* scenario. See Experimental procedures for more information.

Across all industries with labor demand growth, we predict an increase in demand of about 633,000 workers by 2034 compared to the *reference* scenario. In the same time period, 52,000 jobs are lost in industries with a decrease in demand, giving a net growth of around 580,000 workers by 2034. In testing the sensitivity of our analysis against some of the key uncertainties in the modeling (see SM Section D.6) we find that the net growth in the number of workers at the peak in 2034 can be between 450,000 and 800,000, with 580,000 being our base case.

To put our estimates in perspective, a total change of 685,000 jobs (633,000 growth plus 52,000 decline) accounts for just 0.4% of the current US employment and roughly 0.15% of the estimated US labor market flux within 15 years.[3] Not all job transitions are occupational transitions: Vom Lehn et al. (2022) calculates that approximately 5.9% of US workers switched occupations per year between 2000–2018, although in recent times occupational switching appears to have slowed down. While a change of 685,000 workers may seem small with respect to total employment and labor flows, job changes caused by the energy transition could be highly geographically concentrated (Lim et al., 2023). Therefore, there may be skill shortages within regions where jobs are created and a concentration of displaced workers where jobs are lost. While the former may slow down the transition, the latter can

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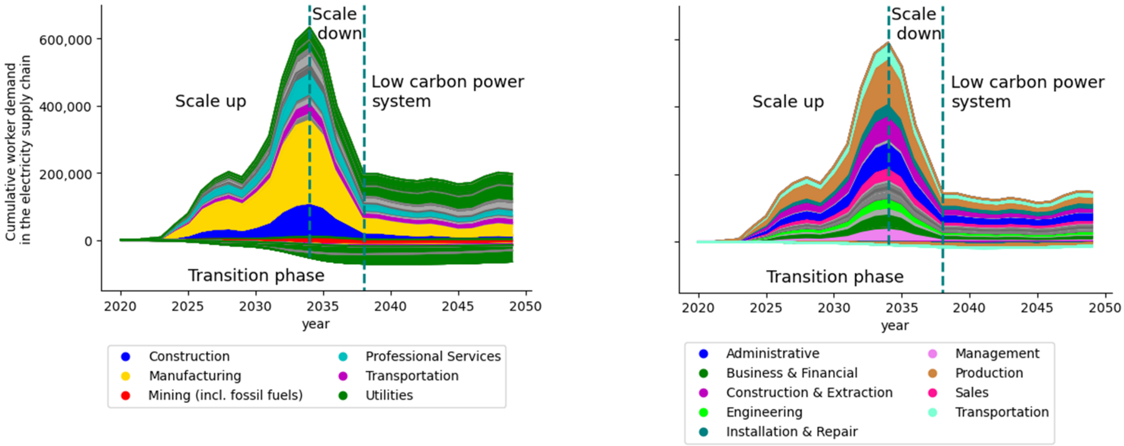
[3] In June 2023, there were 161 million employed workers in the US, and the annual firm-level job reallocation rate is roughly 20% (2011 data in figure 3 in Davis and Haltiwanger, 2014).

lead to local economic decline and rising political discontent (Dijkstra et al., 2020). Furthermore, the US labor market is still relatively tight with low unemployment and a high number of vacancies (Ferguson, 2024), which can make additional skill shortages harder to absorb.

An important contribution of this study is the temporal dimension of labor demand and skill mismatch, both during the electricity sector transition and beyond. We focus on the heterogeneity of temporal trajectories for demand of detailed industries and occupations.



(a) Industries

(b) Occupations

Figure 2: **Total additional demand change for workers in the 95% decarbonization by 2035 scenario.** (a) Per aggregated industry and (b) per occupation category. The demand change is net of the NREL *no-new-policy reference* scenario. Industries are plotted at the detailed level used in the analysis (82 industries) but colored by their 2-digit aggregated categories (14 of 20 categories are minimally affected and shown in gray scale[4]). Occupations are plotted at the detailed level used in the analysis (539 occupations) and colored by their 2-digit level aggregation (13 of 22 occupation groups are minimally affected and shown in gray scale[5]). Different phases of the transition are demarcated with dotted vertical lines and labeled.

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[4] Gray-scale industry categories are: 'Accommodation and Food Services', 'Administrative and Support and Waste Management and Remediation Services', 'Agriculture, Forestry, Fishing and Hunting', 'Arts, Entertainment, and Recreation', 'Educational Services', 'Finance and Insurance', 'Health Care and Social Assistance', 'Information', 'Management of Companies and Enterprises', 'Other Services (except Public Administration)', 'Public Administration', 'Real Estate and Rental and Leasing', 'Retail Trade', 'Wholesale Trade'.

[5] Gray-scale occupation groups are: 'Computer & Maths Occupations', 'Science Occupations', 'Social Service Occupations', 'Legal', 'Education Occupations', 'Arts and Entertainment Occupations', 'Healthcare Practitioners', 'Healthcare Support Occupations' 'Protective Service Occupations', 'Food Preparation and Serving Occupations', 'Cleaning and Maintenance Occupations', 'Personal Care Occupations', 'Farming Occupations'.

Temporal phases of labor demand

Our temporal analysis shows three distinct phases in the demand for labor in the electricity supply chain over the full transition. The first phase, before 2034, is the 'scale-up' phase, in which the work is done to reach the goal of 95% decarbonized electricity generation by 2035. It includes an increase in overall demand for labor, mainly driven by the need to replace existing fossil fuel generation infrastructure with renewables and additional electrification. The next phase, between 2034 and 2038, is the 'scale-down' phase, characterized by decreasing overall labor demand as most of the new replacement infrastructure is built. Together, the scale-up and scale-down phases make up what we refer to as the 'transition phase'.

Such fluctuations are not new and are to be expected in large-scale infrastructure projects or technological transitions. For example, railway construction started in Ireland in 1833 and employment grew to over 30,000 workers in 1847 during the *railway mania*. By 1849, the number of workers had fallen back to 10,000–15,000, where it remained until 1860 (Lee, 1979). In a more modern example, BT Group in the UK announced job cuts in 2023 when its fiberglass cable expansion was finished. One labor union representative acknowledged that such job cuts were 'no surprise' given the infrastructure changes (Sandle, 2023).

After the transition phase begins the 'low-carbon power system' phase. While grid expansion continues in this phase until at least 2050, the demand for labor is relatively stable. We estimate the new low carbon power system will have about 117,000 net more employed workers compared to a *no-new-policy reference* scenario (see SM Section D.6 for a sensitivity analysis on this estimate).

When we dive deeper into the industry profile details (Fig. 2a), we find that the largest contributors to the peak in 2034 are the manufacturing and construction sectors, which are crucial for producing renewable energy technologies and deploying the necessary infrastructure. Smaller industries, such as Professional, Scientific, and Technical Services, and Wholesale Trade, also fit within this group. Other industries behave in different ways. Fossil-fuel industries, including some utility industries and Mining, see a net loss of worker demand over the entire period. Such losses could be lessened depending on global demand for US exports, such as possible increases in demand for US natural gas (Jenkins et al., 2022; EIA, 2023). (Also see Section D.6 of the SM for more details on import and export scenarios). Vice versa, utilities that are based on renewables experience a net gain in labor demand.

We map sectoral labor demand changes to 539 occupations, assuming a fixed occupational composition per sector. Fig. 2b shows the labor requirement dynamics per aggregate occupation category. This represents an unconstrained estimate without considering the elasticity of demand or substitution between physical capital and labor. We will discuss potential frictions this causes in the later section *Skills shortages and stranded labor*.

We highlight two results on Fig. 2b: First, as seen by the differences in the mass of color below the x-axis, occupations experience much fewer job losses than industries. This is due to the fact that the same occupations are needed in many different industries. For workers in such occupations, the transition might involve a change of firm and sector, but not necessarily a change in occupation.

Second, while it is apparent that industries experience different temporal employment dynamics (e.g., compare manufacturing vs. utilities vs. mining), most of the 22 occupational categories move through the transition more or less in tandem. In the next section, however, the heterogeneity becomes apparent at the more detailed occupation level.

Temporal typology of occupational demand change

To better understand skill mismatches, we study the temporal dynamics of different occupations. In Fig. 3, we plot the change in demand for all occupations during the initial scale-up phase against the change in demand during the later scale-down phase of the power system transition.

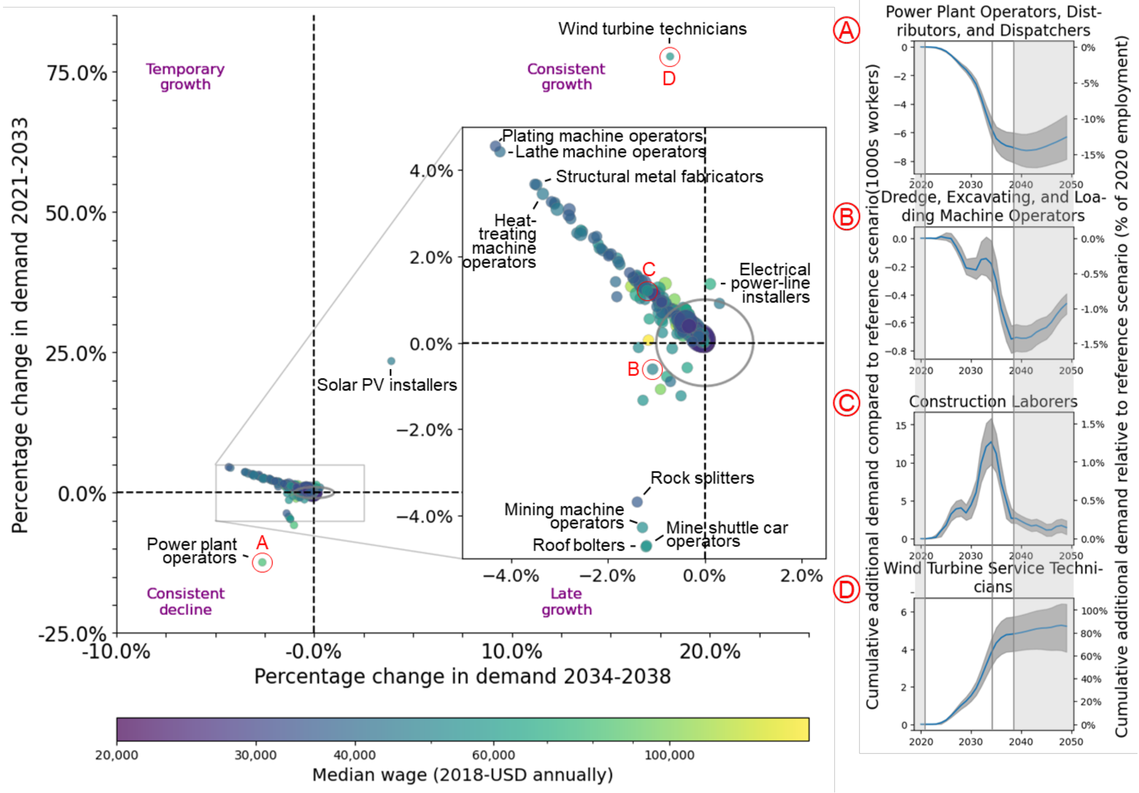

Figure 3: **Occupation demand change relative to employment in the *95% by 2035* scenario.** On the vertical axis, the net demand change between 2021 and 2034 (scale-up phase), and on the horizontal axis, the change between 2034 and 2048 (scale-down phase). The demand change is relative to the *no-new-policy reference* scenario. Three occupations (Wind turbine technicians, Power plant operators, and Solar PV installers) that lie outside of the rectangular zoom-in box are labeled. The zoom-in box does not cover any data point in the main plotting area. Occupations within the gray circle shown in the zoom-in box experience less than 1% demand change and are considered minimally affected; all other occupations are categorized by the labor transition typology that is formed by the four quadrants, which are labeled in purple. Occupations are colored according to their mean wage. The occupational profiles on the right show the full temporal dynamics for four selected occupations. Gray error bars are constructed via the sensitivity analysis on the trajectory calculation (See SM Section D.6).

We classify occupations into five types based on the dynamics of their demand.[6] We classify occupations that lie within the gray circle as ‘minimally affected’. The combined demand change of these occupations in the scale-up and scale-down phases is less than 1% of their 2020 employment level.[7] This group consists of 423 out of the

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[6] The formal definitions of the typology can be found in SM Section B.7. A full list of occupations in each group can be found in SM Section C.9. In Section B.7, we present an alternative definition of the transition groups as robustness check.

[7] We calculate the combined demand change by taking the square root of the sum of squared changes in demand in the scale-up and scale-down phases.

539 occupations, or 88% of total US employment in 2020. The minimally affected occupations include all legal, healthcare and education occupations, and the vast majority of sales, administrative support, management and business workers, among others.

The remaining occupations are classified based on the quadrants in Fig. 3. The top-right quadrant corresponds to the 'Consistent growth' occupations that experience a demand *increase* during *both* the scale-up and scale-down of the electricity transition. This group has only three occupations: solar PV installers, wind turbine service technicians, and power line installers. Relative to the no-new-policy baseline, the demand for solar PV installers is expected to increase by 20% between 2020 and 2038, and the demand for wind power technicians is expected to increase by 80%. To achieve the fast transition scenario, a substantial number of new workers in these occupations needs to be trained.

The bottom-left quadrant corresponds to the 'Consistent decline' group, which experiences a *decline* in demand during *both* the scale-up and scale-down phase. The 13 occupations of this group are mainly employed in mining and extraction and fossil fuel operations. We find some of the largest reductions in demand for power plant workers, roof bolters, mining machine operators, and mine shuttle operators. Note that our analysis focuses on the power sector only and thus does not include other fossil fuel uses, such as direct coal use in the steel sector or fossil fuel-powered vehicles. If the power sector transition is accompanied by a low-carbon transition in other sectors, the decline in these occupations and others in fossil fuel extraction industries will be even more dramatic. On the other hand, some of these losses might be reduced if global demand for US fossil fuel exports, such as US natural gas, increases, as some have predicted (Jenkins et al., 2022; EIA, 2023). (Also see Section D.6 of the SM for more details on import and export scenarios).

The top-left quadrant of Fig. 3 corresponds to the 97 'Temporary growth' occupations that have an increase in demand during the scale-up phase followed by a decline during the scale-down phase. The 'temporary growth' occupations cover more than half of production, construction, and engineering occupations, as well as some installation and maintenance, management, business, and administrative occupations.

Finally, there are no 'Late growth' occupations in the bottom-right quadrant; i.e., there are no occupations that experience a decrease in demand during the scale-up phase and an increase in demand during the scale-down phase.

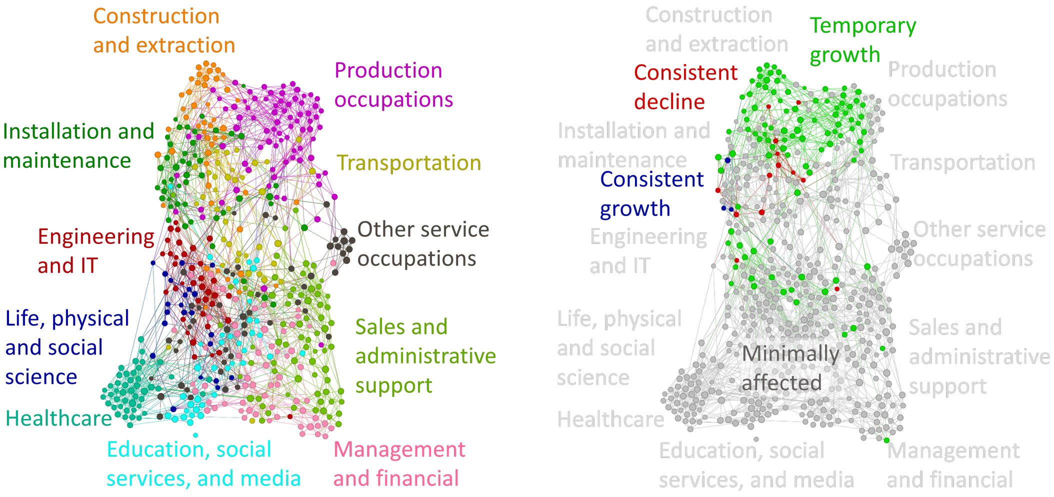
Skill content and overlap with green jobs classifications

Following the methodology developed by Consoli et al. (2016), we examine the skill content of these groups in SM Section D.4.2. We find that the occupations most adversely affected by the transition have higher manual and routine skills. This is particularly true for the 'Consistent decline' occupations. 'Consistent growth' occupations score above average on non-routine interactive skills, and 'Consistent decline' occupations score below average. The other skills (analytical and cognitive) show fewer differences on aggregate. We find a slightly negative correlation coefficient of -0.06 between mean annual wage and 'Temporary growth' occupations. The correlation coefficients between wage and 'Consistent growth' or 'Consistent decline' are less than 0.01.

In SM Fig. S13 in SM Section D.4.1, we map the current location quotients by US state of the occupation typology, which highlights the current geographical differences between some of these occupations. For example, both Wyoming and West Virginia see a strong 'Consistent decline' profile, but Wyoming has more 'Consistent growth' occupations, because it has more installed wind power capacity relative to its population. However, we want to stress that this refers to 2018 data and does not include potential future renewable capacity locations.

As expected, 'Consistent decline' occupations overlap strongly with brown occupations as defined by Vona et al. (2018), and 'Consistent growth' occupations mostly belong to ‘Green new & emerging’ occupations as defined by Dierdorff et al. (2009). ‘Temporary growth’ occupations, however, do not fit neatly into either category.

This challenges the green vs brown dichotomy: the demand pattern of ‘Temporary growth’ occupations is similar to ‘Consistent growth’ occupations for the scale-up phase, but better reflects the pattern of ‘Consistent decline’ occupations during the scale-down phase. We find that ‘Temporary growth’ occupations are included in existing classifications of *both* green and brown occupations. See SM Section D.5 for more information.



(a) (b)

Figure 4: **Network of related occupations.** Nodes represent occupations, and two occupations are connected if workers can switch between them, as defined by the list of related occupations from O*NET. The layout of both networks is the same and is obtained using a force-pull algorithm. In a), the network is colored by broad occupational categories, and in (b) by their temporal profile typology.

Skills shortages and stranded labor

A key focus of this study is to identify skill mismatch frictions that may arise in the scale-up and scale-down phases of the transition. We follow previous work on skill mismatch using skill-relatedness (Bowen et al., 2018; Neffke et al., 2024; Mealy et al., 2018). We use a list of related occupations from O*NET that provides career switching options for each occupation and create an occupational mobility network where the nodes represent occupations. Links are drawn between two occupations if workers can switch between them, similar to the network used in Bowen et al. (2018) (see Experimental procedures and SM Sections A.4 and B.9).

Figs. 4a and 4b show the network structure with the nodes (occupations) colored by eleven broad occupational categories (SM Section A.3.1) and our trajectory-based typology, respectively. Most affected occupations cluster in the upper side of the network, suggesting that the transition affects specific parts of the labor market much more. Because affected occupations are linked, skill mismatch frictions are likely to be present for some occupations.

Overall presence of skill mismatch frictions

We confirm our visual analysis using assortativity, a standard network science metric (see Experimental procedures). Assortativity in networks refers to the tendency of nodes to be connected to other nodes that are like (or unlike) them with respect to specific attributes. Assortativity is a network-wide measure. An assortativity value of 1 means all occupations only link with similarly impacted nodes; a value of 0 indicates random mixing. Thus, a high assortativity value indicates that occupations are only connected to other occupations that face a similar shock, and overall skill-mismatch frictions are high.

Using our typology of 'Consistent growth', 'Consistent decline', and 'Temporary growth' occupations, we find positive and significant assortativity (Table 1). Thus, as suggested by Fig. 4, occupations tend to be connected with other occupations within the same group, rather than with occupations of other groups.

When we calculate the assortativity coefficient directly on the change in demand scale-up phase, we find a positive but relatively low level of assortativity. This indicates that while frictions do exist in the scale-up phase, there are still career options available for workers moving out of shrinking occupations. This concretely means that workers in the 'Consistent decline' group have possibilities to move to occupations in the ‘Temporary growth’ or ‘Consistent growth’ groups.

In contrast, assortativity in the scale-down phase is higher, indicating that career changes from ‘Consistent decline’ and ‘Temporary growth’ occupations to ‘Consistent growth’ occupations are likely to be less common. This means that skill mismatch frictions are of greater concern in the later stages of the transition. The results show that the network exacerbates the labor market impacts of the different phases of the transition but that these impacts are not static – they evolve.[8]

	Assortativity
Occupational typology (Consistent decline, Consistent growth, Temporary growth)	0.43†
2021–2034: Demand change during the scale-up phase	0.05†
2035–2038: Demand change during the scale-down phase	0.26†

Table 1: **Assortativity of labor demand during the transition.** The dagger (†) indicates results that are greater than for a randomized shock in 99.9% of simulations in a Monte Carlo simulation (see Experimental procedures for details).

Skill-mismatch consequences for individual occupations

Skill mismatch frictions can affect both the supply and demand side of the labor market. An increase in demand for an occupation as well as for its related occupations (neighbors) means employers will find vacancies harder to fill. Conversely, a decrease in demand for an occupation and its related occupations can make it harder for displaced workers to find new employment. We therefore look at both frictions in moving away from one’s occupation to other occupations (its *out-neighbors*), and frictions in attracting workers to an occupation from other occupations (its *in-neighbors*). For occupations that see a decline in demand, out-neighbors are important. Vice versa, in-neighbors are important when considering occupations that experience demand growth.

To highlight occupations most affected by skill-mismatch frictions during the first phase of the transition, we plot in Fig. 5 the demand change for the scale-up

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[8] In SM Section D.4.3, we show that our results are robust when we use an occupational network based on empirically observed occupational changes rather than O*NET’s measure of relatedness. In SM Section D.6, we also explore how IO model assumptions affect the assortativity levels.

phase against the demand change for the pool of workers in related (neighboring) occupations. Frictions are strongest in the gray areas of this figure, where the demand change for individual occupations is similar to the demand change for its neighbors.

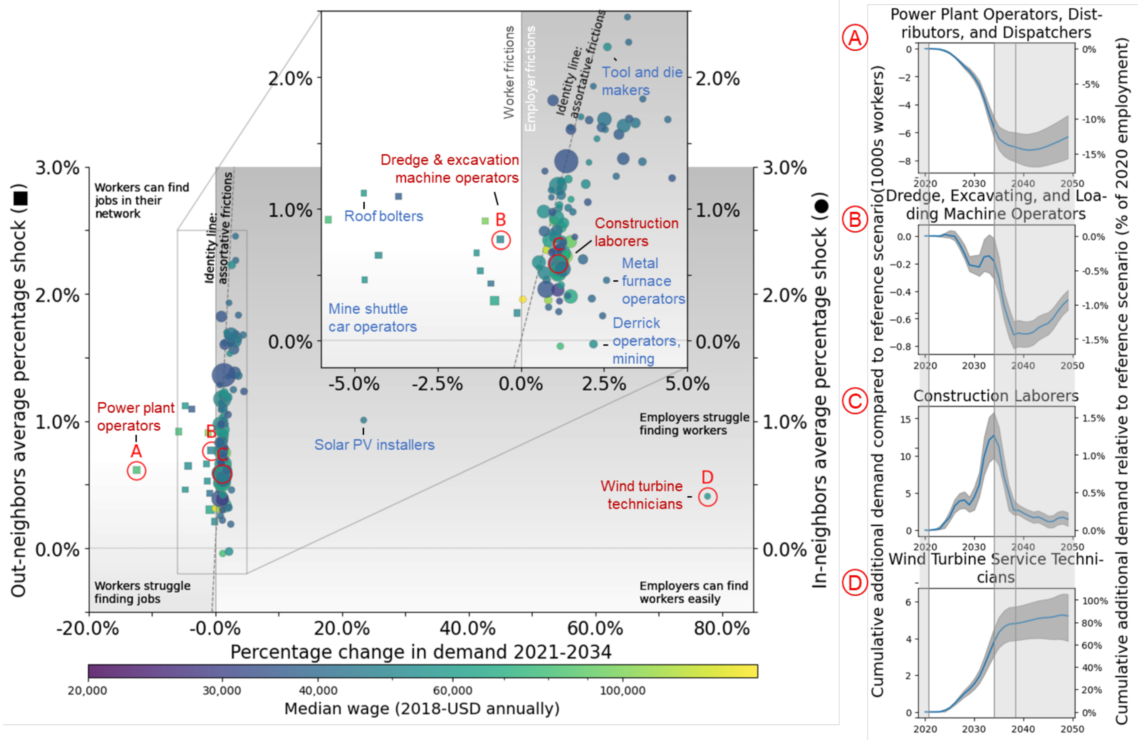

Figure 5: **Skill mismatch frictions during the scale-up phase.** Scatter plot of demand change in the scale-up phase (2021-2034) per occupation (x-axis) and their neighbors (y-axis) in the *95% by 2035* scenario, relative to the *no-new-policy reference* scenario. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation α are related occupations: they form potential career switching options for workers in α. Data points using out-neighbors are shown with squares. Vice versa, in-neighbors of α are occupations for which α is a related occupation: workers in those occupations see α as a potential career switching option. Data points using in-neighbors are shown with circles. In- and out-neighbors are not necessarily the same. The identity line is shown with a dashed line, and selected occupations are highlighted. Three occupations (Wind turbine technicians, Power plant operators, and Solar PV installers) that lie outside of the rectangular zoom-in box are labeled. The zoom-in box does not cover any data point in the main plotting area. The intensity of background shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$. The gray scaling is a linear function of the neighborhood shock, when the sign of the demand change for individual occupations is the same as for its neighbors (i.e., top right and bottom left quadrants). On the right of the main plot, demand change profiles over time are shown for occupations highlighted in red. The four quadrants are labeled by the main effect of the occupational network faced by each occupation.

The figure is split along the $x = 0$ line. On the left side of the $x = 0$ line, the darker shading indicates increased frictions for workers: that is, it becomes harder for displaced workers to find new employment. We thus compare the average shock to occupations with their out-neighbors on the y-axis. These data points are shown as squares in Fig. 5. For a given occupation α, out-neighbors are related occupations: they form potential career switching options for workers in α.

Vice versa, on the right side of the $x = 0$ line, the darker shading indicates increasing employer frictions: that is, it becomes harder for employers to fill vacancies. Here, we compare the shock to occupations with the average shock to their in-neighbors. These data points are shown as circles. Again, for a given occupation α, in-neighbors are occupations for which α is a related occupation: workers in those occupations see α as a potential career switching option. In- and out-neighbors can overlap but are not necessarily the same.

Along the identity line, occupational frictions are aligned assortatively, and an occupation is as affected as their neighboring pool of related occupations. In other words, for occupations along the identity line, labor market pressure caused by the transition cannot easily be alleviated by switching occupations or headhunting workers with compatible skills. Farther away from the $x = 0$ line, shocks to individual occupations can be partially alleviated by switching between occupations.

During the scale-up phase, most of the skill mismatch frictions affect employers struggling to find suitable workers, including for manufacturing occupations such as ‘Tool and die makers’, construction occupations such as ‘Construction laborers’, and renewable operations workers such as ‘Wind turbine service technicians’. ‘Derrick, rotary drill and service unit operators, mining’ see an increase in demand in this phase, but its neighbors, on average, see a very small decline, suggesting an availability of workers to fill vacancies.

Some occupations, such as ‘Roof bolters’ and ‘Power plant operators’, see their demand decrease, but experience a milder overall impact as demand increases in their pool of out-neighboring related occupations, meaning the network helps alleviate (part of) the direct negative impact.

In the scale-down phase, as shown in Fig. 6, the situation is reversed. In contrast to the scale-up phase, displaced workers in many occupations, excluding the minimally affected, will struggle to find compatible jobs in the scale-down phase. The construction and manufacturing occupations, as well as mining and fossil fuel workers, all see a decline in demand, as well as a decline in demand for occupations with similar skills (that they might be able to transition to).

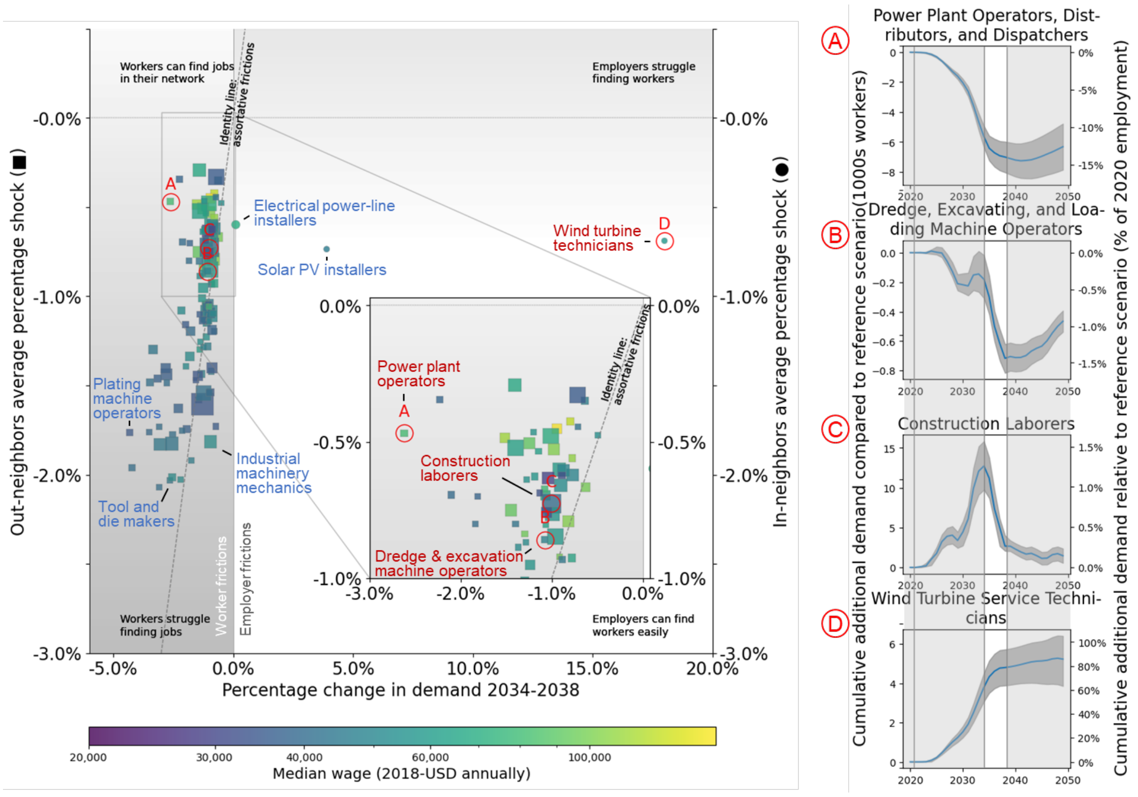

Figure 6: **Skill mismatch frictions during the scale-down phase.** Scatter plot of demand change in the scale-down phase (2034-2038) per occupation (x-axis) and their neighbors (y-axis) in the *95% by 2035* scenario, relative to the *no-new-policy reference* scenario. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation α are related occupations of α: they form potential career switching options for workers in α. Data points using out-neighbors are shown with squares. Vice versa, in-neighbors of α are occupations for which α is a related occupation: workers in those occupations see α as a potential career switching option. Data points using in-neighbors are shown with circles. In- and out-neighbors are not necessarily the same. The identity line is shown with a dashed line, and selected occupations are highlighted. The zoom-in box does not cover any data point in the main plotting area. The intensity of background shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$. The gray scaling is a linear function of the neighborhood shock, when the sign of the demand change for individual occupations is the same as for its neighbors (i.e., top right and bottom left quadrants). On the right of the main plot, demand change profiles over time are shown for occupations highlighted in red. The four quadrants are labeled by the main effect of the occupational network faced by each occupation.

We find that many of these occupations align along the identity line of assortative frictions, confirming the relatively large assortativity coefficient for the scale-down phase in Table 1. Solar PV installers and wind turbine service technicians still face large demand increases but see some of the hiring difficulties alleviated because demand declines in their neighborhood, albeit to a limited extent. Thus, successfully managing the power system decarbonization will involve policies aimed at supporting workers to switch from 'Temporary growth' and 'Consistent decline' occupations into 'Consistent growth' or minimally affected occupations.

We find no relationship (Pearson correlation coefficients are smaller than 0.05) between mean annual wages and an increase or decrease in demand in the scale-up or scale-down phases. This means that, while specific occupations with low or high wage may be impacted, the temporal dynamics of the transition may have limited effects on the overall mean wage.

The six occupations most closely related (in-neighbors) to *Wind turbine service technicians* are *Energy engineers*, *Solar PV Installers*, *Power Plant Operators, Distributors, and Dispatchers*, *Pipelayers, Plumbers, Pipefitters, and Steamfitters*, *Installation, Maintenance, and Repair Workers, All Other*, and *Industrial Production Managers*. Using these neighboring related occupations, we can see how Figs. 5 and 6 relate to Figs. 3 and 4. For example, in Fig. 3, wind turbine service technicians are in the 'Consistent growth' quadrant, and Power plant operators in the 'Consistent decline' quadrant. Wind turbine service technicians are part of *Installation, repair, and maintenance* occupations, and Power plant operators are part of *Production occupations* in Fig. 4a, but these two occupations are connected and are placed close together in the network in Fig. 4b. Because wind turbine technician is an out-neighbor of power plant operators, and, vice versa, power plant operators is an in-neighbor of wind turbine technicians, they influence each others' y-axis value in Figs. 5 and 6. In particular, the connection between the two occupations increases the out-neighbors' average shock of power plant operators and lowers the in-neighbors' average shock of wind turbine service technicians, lowering skill-mismatch frictions for both.

Occupations most closely related to *solar PV Installers* are similar to those related to wind turbine service technicians, but, in addition, include *Electricians*, *Broadcast and Sound Engineering Technicians and Radio Operators*, *Construction and Building Inspectors*, and *First-Line Supervisors of Construction Trades and Extraction Workers*.

Beyond 2038, the demand for workers remains higher than the *reference* scenario and is relatively stable, although demand is much lower than at the peak of the scale-up phase. This increase in demand for workers arises for two reasons. First, grid expansion is ongoing until at least 2050 (SM Fig. S2). Second, the scenario foresees an increase in both capacity and demand for electricity relative to the *reference* scenario, which increases the overall demand for labor.

Robustness of results

As we show in detail in the Experimental procedures and SM Section D.6, we have extensively tested the sensitivity of our model and found that our results are robust with respect to a number of important assumptions (fixed IO coefficients and cost vectors, industry-occupation composition, etc.) We have also identified two key sources of uncertainty in our analysis.

Firstly, lower labor requirements from transmission and distribution investments (e.g., due to higher levels of innovation and automation) could lead to lower employment in the electricity supply chain, bringing them almost on par with the *no-new-policy reference* scenario. This would affect occupations related to transmission and distribution most strongly, such as Electrical power-line installers.

Secondly, the fraction of imports and exports can change during the transition, which impacts the demand for labor. As mentioned in the introduction, our main scenarios reference everything to 2018 levels, keeping the *relative share* of imports fixed and *absolute size* of exports fixed. The underlying logic for the inconsistent treatment of imports and exports is motivated by two facts: first, NREL's *95% by 2035* scenario concerns the transition in the US only. If the US shifts from the *reference* scenario path to the *95% by 2035* scenario, but the rest of the world does not change course and import and export shares remain constant, the US will import more in absolute terms but exports will remain the same. Second, our results are presented relative to a no-new-policies reference scenario. Potential imports and export changes that affect both the reference scenario and the US 95% by 2035 scenario equally cancel each other out in our results. If, however, the US changing course to the 95% by 2035 scenario *induces* the rest of the world to also increase the pace of the power sector transition, our assumptions about imports still correspond to "all else being equal", but our assumptions about US exports might be pessimistic because US exports would become smaller in *proportional* terms, corresponding to a situation where US manufacturing becomes less competitive, relatively speaking, than it is now.

To deal with these uncertainties, we investigate four alternative scenarios. In broad outlines, in order of most pessimistic about changes to US competitiveness to most optimistic, these are:

1. The *share* of US imports *increases* by 50% while exports remain constant.
2. The *share* of US imports *decreases* by 50% while exports remain constant.
3. The *share* of US imports remains constant while the exports, compared to 2022 levels, double to triple in 2030 and increase four to nine-fold in dollar terms by 2040, depending on how 2022 export data is interpreted (this is also consistent with a scenario in which the global market for renewables increases by a factor of four to nine and the US share of this market remains constant).
4. The *share* of US imports *decreases* by 50% while exports *increase* as in scenario

(3) above.

These are stylized scenarios, but we have chosen the magnitude of import share changes in the alternate scenarios to be roughly in line with the historical behavior, as seen in Fig. S4 in SM Section C.2. To put this in perspective, between 1997 and 2014, the import share of Computer and electronic product manufacturing went from 33% to 54% in 2014 and then declined to 44% in 2018. It is conceivable that the results of the Inflation Reduction Act (IRA), which has the ambition to increase US domestic manufacturing (The White House, 2022), or other legislation will increase US production beyond any of our scenarios here. Regardless of whether such a rise in US exports occur, our qualitative conclusions remain robust in the four alternative scenarios that we tested, as shown in Fig. S20 in Section D.6 of the SM: relative to the reference scenario, the variation in the total number of jobs in our model between the most pessimistic and most optimistic scenarios ranges from about 560,000 to 630,000 in 2034, and ranges from about 40,000 to 270,000 in 2045.

Discussion and conclusion

The transition to a world powered by renewable energy will involve a transformation of part of the labor market. In this work, we couple a dynamic IO model with a network analysis of occupational mobility and show that such a transition has the potential to generate temporal labor market fluctuations and skill mismatches.

We make three contributions to the wider debate on the labor market impact of the green transition. First, we find more jobs will be created than lost in the US during the initial part of the renewable electricity transition – which is in line with previous research – but we also find that a large fraction of these new jobs will only be required during the scale-up period of the fast transition. The labor market dynamics will change throughout the transition phase until the new stable decarbonized energy system is in place. These dynamics are missed if the scale-down phase and a new stable decarbonized energy mix phase are not included in the time horizon.

Second, in addition to the direct effects on occupational labor demand, we show that there are important secondary effects if related occupations are affected in similar ways. This creates skill mismatches, especially in the later stages of the transition. In the initial scale-up phase, we find the potential for skill shortages that could jeopardize the speed of the transition. In the later scale-down phase, we anticipate that related occupations experience similar demand declines, negatively affecting workers' ability to find jobs. Temporal skill mismatches have received limited attention in the literature but are important when considering the employment impact of the transition.

Third, we identify a fourfold occupational typology based primarily on the scale-up and scale-down phases of the transition. Besides the large group of mostly unaffected occupations, a small number of occupations see a sustained growth in demand, a larger group sees a consistent decline, and most occupations that are affected experience a temporary rise in demand during the scale-up and an almost equal decrease in demand after the electricity sector reaches its decarbonization target.

The green and brown jobs dichotomy cannot fully capture the temporal dynamics of the electricity sector transition. We find that the occupations that experience only temporary growth do not fit neatly in either category, overlapping with both brown jobs from Vona et al. (2018) and green jobs from Dierdorff et al. (2009).

More specifically, the demand pattern of 'Temporary growth' occupations is similar to 'Consistent growth' occupations for the scale-up phase, but better reflects the pattern of 'Consistent decline' occupations during the scale-down phase. Workers in such occupations will be vital to ensuring the renewable electricity transition happens quickly, but additional care needs to be taken to manage their long-term career trajectories.

Compared to the estimates in previous literature, as spelled out in the Introduction, our results are in line with Xie et al. (2023)'s estimate of US employment changes due to power sector decarbonization (439,000 net jobs) and the ILO's estimate for the Americas as a whole of an IEA scenario to keep warming below 2°C (ILO, 2018) (∼700,000 net US jobs). Conversely, our estimates are roughly an order of magnitude lower than those reported by Jacobson et al. (2015) (∼2 million), Mayfield et al. (2023) (∼1.5–6 million), or Ram et al. (2022) (∼4 million). This discrepancy is in part due to the fact that these studies include the entire energy sector, rather than just the electricity sector. Some also do not report results relative to a *reference* scenario, which in our case already contains substantial decarbonization, or have their headline results aggregated over a longer time period. Thus, while we look at a subset of changes, the effects we uncover may be amplified when considering the entire energy sector or longer time periods.

Our results are derived specifically for the US. Other countries have different economic structures and, hence, results should not be extrapolated. For example, in a study by the ILO (2018), the change in labor demand ranges from +0.45% of the workforce (Americas) to -0.48% (Middle East) for a scenario consistent with limiting warming to 2 °C. Likewise, Jacobson et al. (2017) report global net job growth for a scenario with 100% renewable energy by 2050, but also find that net job losses are possible for some fossil fuel producing countries. Furthermore, the scope and pathway of emission reduction will differ per country. For example, while energy is the major source of emissions in most countries, in Brazil it is deforestation and agriculture, as its energy sector is already highly decarbonized (Berryman et al., 2023).

The rapid transition scenario considered here involves a non-marginal increase over the *reference* scenario in demand for three key 'Consistent growth' occupations: solar PV installers, wind turbine service technicians, and power line installers. Given that the skills needed for these occupations will be in high demand during the scale-up, it will be important to ramp up training in anticipation of such shortages to avoid bottlenecks slowing down the transition. To find how much the transition may be slowed by such skill shortages, the occupational bottlenecks would need to be coupled with, or incorporated endogenously in the energy-economy model that produces the transition scenario.

Our sensitivity analysis in the Experimental procedures and SM Section D.6 tests and discusses the most important assumptions in our model, including changes to import and export assumptions and transmission and distribution (T&D) cost calculation. In our main scenarios, we keep import fractions at the industry level constant and exports constant in absolute value. But if the US's international competitiveness in green technologies could be improved by a fast transition, this could alleviate some of the difficulties for workers in the domestic scale-down phase. Similarly, growing natural gas exports could limit the negative impact on some fossil fuel workers (Jenkins et al., 2022; EIA, 2023). The continuing cost declines of renewables is another important consideration. We take our projections from NREL's ATB, but recent research using empirically grounded technology learning curves suggests that we might see even more aggressive cost declines for renewables and storage in the future (Way et al., 2022; Creutzig et al., 2023), especially with additional policies such as the IRA. In our sensitivity analysis, more advanced cost curves lead to lower demand growth for labor in the power sector supply chain. While cost curves for some technologies are well documented, estimating future cost and labor requirements for grid expansion is challenging due to limited available estimates in the literature.

Cost curves affect our labor demand estimates directly, because we assume a fixed ratio of workers per constant-dollar of cost. This suggests a cost-breakdown neutral path of innovation, where productivity is fixed in monetary units (USD output per worker) but can change in energy units (GW(h) output per worker). We provide some empirical evidence on this assumption in SM Section C.6 and discuss further methodological assumptions in SM Section B.1.

We have demonstrated an approach that can provide valuable insights into the labor market frictions associated with a major transition, applied to the US power sector. This method is relatively simple, transparent and generic, yet can give granular results. Our approach naturally incorporates cost-reduction forecasts and can be easily extended with more data granularity.

In light of the heterogeneous demand trajectory types that we have identified and the need for rapid decarbonization, we conclude that the transition requires enlightened management to minimize skill mismatch for displaced workers and skill shortages in filling vacancies. For example, targeted retraining programs can make additional transition options become feasible and alleviate pressure on certain occupations.

Monitoring how workers make career decisions during the transitions can help *validate* our skill mismatch results. Empirical transition data from national surveys and CV repositories have been used to show that occupational similarity translates into how workers move between them (Mealy et al., 2018; Frank et al., 2024). Future work could employ a similar approach to validate the frictions identified in this work with future empirical data.

Our method is sufficiently simple that it can and should be applied regularly as new data and insights on labor market changes become available. Likewise, the convergence of different perspectives regarding future technological selections will enhance scenario refinement and subsequently improve the results. Early identification of the potential causes of labor stranding and shortages can enable policymakers to effectively help workers and employers tackle these frictions, thereby making the green transition happen faster and more equitably, and ultimately reducing the global warming that future generations must face.

Experimental procedures

Methods approach

We followed a 4-step framework that couples a power transition scenario (step 1) with a dynamic input-output model to estimate upstream impacts (step 2), applying detailed occupational employment data (step 3) and an occupational mobility network (step 4) to assess labor market frictions. The approach is pictured stylistically in Fig. 7, and each of the steps are described in detail below. To focus specifically on the labor impacts of the low carbon transition, all of our results are shown as relative to a *no-new-policy reference* scenario (which is translated into our framework using the same four-step procedure). In SM Section D.3, we present some of the results relative to the year 2020, rather than those relative to the *no-new-policy reference* scenario that are shown in the main text. Additionally, in SM Section D.2, we show implications for the more gradual *95% by 2050* scenario.

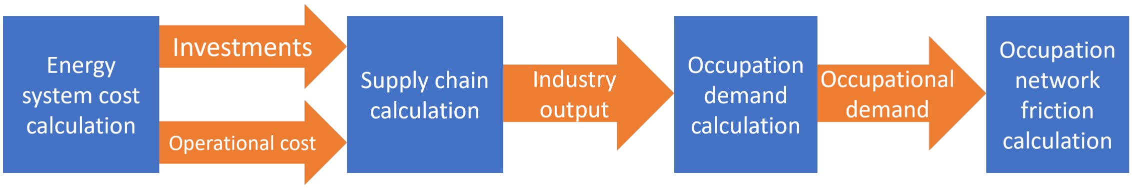

Figure 7: **Overview of our four-step methodology.** First, we calculate the cost of the power sector decarbonization, both in terms of capacity changes (investments), and electricity production (operational costs) of different technologies. The IO model then calculates the direct and upstream supply chain changes in terms of industry output and, subsequently, demand changes for workers per occupation. Finally, we use occupational networks to calculate skill mismatch and skill shortage frictions.

Step 1: Energy and cost scenarios

The first step in our approach involves quantifying future technology-specific expenses for electricity generation sectors. We achieve this by combining the scenarios of future electricity capacity and generation with exogenous projections of unit costs for various detailed electricity technologies. For our analysis, presented in the main text, we utilize the exogenous deployment and cost trajectories from the fast decarbonization scenario (*95% by 2035*) outlined in NREL's *2021 Standard Scenarios Report: A US Electricity Sector Outlook* (Cole et al., 2021).

For each scenario, we map the deployment (capacity and generation) of 19 technologies and unit cost projections of 17 technologies onto 10 electricity generation and supporting sectors (coal, natural gas, biomass, geothermal, hydro, nuclear, solar, wind, battery storage, and transmission and distribution (T&D)), as explained in detail in the SM Section C.1. Since investments and operational expenses affect the input-output model differently (see Step 2 below), we consider capital expenditure (capex) and operational expenditure (opex, which consists of variable and fixed opex, and fuel cost) separately. See SM Section B.4 for more details on why we make this cost component disaggregation.

More formally, let $c_{i,t}^{j}$ denote the unit cost projection of electricity generation technology i of a given cost category j for the year t. We obtain the total annual costs $C_{i,t}^{j}$ for each cost category j as

$$
\begin{aligned}
C_{i,t}^{\text{fix opex}} &= Y_{i,t} c_{i,t}^{\text{fix opex}}, && (1)\\
C_{i,t}^{\text{var opex}} &= X_{i,t} c_{i,t}^{\text{var opex}}, && (2)\\
C_{i,t}^{\text{fuel}} &= X_{i,t} c_{i,t}^{\text{fuel}}, && (3)\\
C_{i,t}^{\text{opex}} &= C_{i,t}^{\text{fix opex}} + C_{i,t}^{\text{var opex}} + C_{i,t}^{\text{fuel}}, && (4)\\
C_{i,t}^{\text{capex}} &= \max\left\{(Y_{i,t} - Y_{i,t-1} + R_{i,t-1}), 0\right\} c_{i,t}^{\text{capex}}, && (5)
\end{aligned}
$$

where $Y_{i,t}$ is the installed capacity of technology i at t in MW, $R_{i,t}$ the retired capital stock in MW and $X_{i,t}$ the generated electricity in MWh. The maximum operator in Eq. (5) avoids negative investment values when total installed capacity declines.[9] Note that capex and fixed opex unit costs are measured in USD per MW, whereas variable opex and unit costs are given in USD per MWh.

Since scenarios generated by power system optimization models can lead to sub-

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[9] Due to data constraints, we calculate opex and capex for battery storage and T&D differently; see SM Sections B.3 and B.2, respectively.

stantial year-on-year fluctuations in installed capacities, we avoid overly erratic job impacts by smoothing the total technology-specific cost estimates using 3-year moving averages. In SM Section D.6, we discuss the impact on our results of removing this smoothing or extending it to a 5-year moving window.

Step 2: Input-output model

In the second step, we feed the capex and opex estimates of the previous step into a demand-driven input-output (IO) framework to calculate the output changes throughout the electricity sector and its upstream supply chain. We consider a standard domestic demand-driven IO model where the total output $x_{i,t}$ of industry i at time t can be described as the weighted sum of final demand $f_{i,t}$ and the intermediate demand of other industries:

$$x_{i,t} = \sum_{j=1}^{n} a_{ij,t} x_{j,t} + f_{i,t}, \tag{6}$$

and in matrix notation:

$$x_t = A_t x_t + f_t. \tag{7}$$

The technical coefficient matrix (also called 'IO table') A with elements $a_{ij,t}$ stipulates the fixed amount of input i required to produce one unit of output j (Blair and Miller, 2009).[10] By defining the Leontief inverse $L_t = (\mathbb{I} - A_t)^{-1}$, and taking the time difference of Eq. (7), we can write

$$\Delta x_t = L_t f_t - L_{t-1} f_{t-1}, \tag{8}$$

which demonstrates that industrial gross output can change over time as a result of changes in final demand (Δf_t) or/and of changes in the IO network (ΔA_t). We model both components explicitly by mapping capex and opex, computed in Step 1,

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[10] In our study, IO table A and final demand vector f refer to their *domestic* versions. See SM Section B.5 for how we calculate them using the official IO data.

onto the final demand f_t and the IO table A_t, respectively. Note that this approach explicitly calculates the alteration in input structure within the electricity sector as different electricity technologies replace each other, while maintaining constant input coefficients for other sectors. We do not directly account for Keynesian income and consumption effects stemming from shifts in wages or electricity prices. Consequently, our model focuses on direct and indirect effects while disregarding *induced* impacts.

Mapping electricity costs to the IO framework

Changes to electricity technology capex from Eq. (5) lead to changes in final demand in the IO framework. Changes to the electricity technology opex in Eq. (4) instead rewire the intermediate expenses. We require that every electricity generation technology is represented as a separate sector in the IO data. In SM Section B.6, we discuss how we disaggregate the energy sector for that purpose.

Capex. Let K_{ij}^{capex} be the fraction of $C_{i,t}^{\text{capex}}$ (technology i's capex) that is spent on industry j,[11] and let m_i be the fraction of capex that is imported from a foreign industry i.[12] The capex of technology i spent on the domestic industry j is then

$$\widehat{K}_{ij}^{\text{capex}} = (1 - m_j) K_{ij}^{\text{capex}}. \tag{9}$$

The total domestic final demand in industry i due to capex in technology j follows then as

$$f_{i,t}^{\text{capex},j} = C_{j,t}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}}. \tag{10}$$

---

[11] We list the values that we use for all capex cost vectors K_{ij}^{capex} in SM Section C.3

[12] The calculation for m_i can be found in SM Section C.2. That section also discusses the changes in import fraction that happened between 1997–2019.

Summing over all technologies results into

$$f_{i,t}^{\text{capex}} = \sum_j C_{j,t}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}}. \tag{11}$$

We assume all capex is created in the year it comes online, such that the impact on the industry output at time t is

$$\Delta x_t^{\text{capex}} = L_t f_{i,t}^{\text{capex}} - L_{t-1} f_{i,t-1}^{\text{capex}}. \tag{12}$$

Opex. We use the opex in year t to update the base year IO matrix A_{2018} to A_t (with elements $a_{ij,t}$) as follows: industry i's production requirement for electricity generated by technology j is

$$a_{ji,t} = a_{ji,2018} \frac{C_{j,t}^{\text{opex}}}{C_{j,2018}^{\text{opex}}}. \tag{13}$$

We perform a similar shift on the opex part of final demand f_t^{opex} at time t. Final demand at time t for the opex of electricity generation technology j is $f_{j,t}^{\text{opex}} = f_{j,t-1}^{\text{opex}} C_{j,t}^{\text{opex}} / C_{j,t-1}^{\text{opex}}$. We assume here that the final demand for electricity is proportional to the total operational cost, which assumes a fixed and constant markup. The change in output per industry between time $t-1$ and t becomes, following Eq. (8):

$$\Delta x_t^{\text{opex}} = L_t f_t^{\text{opex}} - L_{t-1} f_{t-1}^{\text{opex}}. \tag{14}$$

Total effect of opex and capex. To quantify the total change in sectoral output in a given year, we combine Eqs. (8), (12) and (14) to:

$$\Delta x_t = \Delta x_t^{\text{opex}} + \Delta x_t^{\text{capex}} = L_t \left(f_t^{\text{opex}} + f_t^{\text{capex}}\right) - L_{t-1} \left(f_{t-1}^{\text{opex}} + f_{t-1}^{\text{capex}}\right). \tag{15}$$

Step 3: Modelling occupational demand impacts

We assume that demand for workers per occupation changes proportionally to industry output, i.e., the number of jobs in a given occupation per constant-price USD output of an industry is fixed through time. This means that we allow for proportionally fewer jobs per MW(h) if innovation pushes real prices down. We show in SM Section C.6 some empirical evidence for this proportionality in the solar and wind cost breakdown. In Section D.6, we show how our results depend on the speed of such cost reductions.

Let M be the matrix of workers per output, where M_{ij} is the number of workers in occupation i working for industry j per constant-USD output. We calculate the total demand change Δo_t for workers per occupation between time $t-1$ and t with Eq. (15) as

$$\Delta o_t = M \Delta x_t \tag{16}$$

where $\Delta o_t = [\Delta o_{1,t}, \ldots, \Delta o_{m,t}]$ and each elements $\Delta o_{i,t}$ is the demand change for workers in occupation i between time $t-1$ and t.

Skills and location quotient We follow Consoli et al. (2016) for our calculation of skill content per occupation (see SM Section D.4.2). In SM Section B.8, we explain how we calculate the location quotients of occupation-state pairs.

Step 4: Occupational network and frictions

We quantify occupational skill mismatch frictions using measures derived from network science. We will first define the occupation network, then define network-wide assortativity measures, and finally our local neighborhood-friction measure. We are concerned with frictions caused by the reallocation of workers between occupations. Any frictions arising from job transitions between industries within the same occupation are not considered but could be significant if a geographic relocation is required or industry-specific knowledge is important (Lankhuizen et al., 2023).

Network of related occupations

The related occupation network is a directed network $G(V, E)$ where the nodes V are occupations and the edges E contain a link between occupations i and j if j is a related occupation of i. We construct this network using data on *related occupations* from O*NET (see SM Section A.4 for further details). The network is defined by the adjacency matrix R with items $R_{ij} = RelOcc_{ij} / \sum_j RelOcc_{ij}$, where $RelOcc_{ij} = 1$ if j is a related occupation of i according to O*NET, and 0 otherwise. O*NET determines relatedness between occupations by comparing the similarity in: tasks and work activities, knowledge importance, and job titles (Dahlke et al., 2012). Note that this network is not necessarily symmetric.

Assortativity

We formalize a measure of overall frictions using assortativity. In network science, assortative mixing refers to the inclination of nodes to be connected if they are similar with respect to specific characteristics. We study assortative mixing of the demand change for occupations during the scale-up and scale-down phase, and for the demand trajectory typology we identify in this study.

Assortativity is a network-wide property. We say that a network is assortative if a significant fraction of the edges in the network connect similar nodes or nodes that are of the same type. In an unweighted network, we can compute the assortativity coefficient (Newman, 2018), which is equivalent to a Pearson correlation between connected nodes' attributes. The attributes we are interested in are the demand change, a continuous variable, and our demand trajectory typology, a categorical variable. In our analysis we use weighted continuous assortativity and weighted categorical assortativity, which are extensions to the assortativity coefficient for weighted networks with continuous and categorical variables, respectively.

We also define a local node assortativity metric that we use to highlight frictions for individual occupations.

Weighted continuous assortativity We use an extended version of this coefficient for weighted and directed networks; see also Yuan et al. (2021). This gives the following assortativity coefficient $\rho_{s,x}$ between the edge weights s and continuous node value x for a weighted and directed network G:

$$\rho_x = \frac{\sum_{ij}\left(R_{ij} - \frac{s_i^+ s_j^-}{W}\right) x_i x_j}{\sqrt{\sum_{ij}\left(s_i^+ \delta_{ij} - \frac{s_i^+ s_j^+}{W}\right) x_i x_j \sum_{ij}\left(s_i^- \delta_{ij} - \frac{s_i^- s_j^-}{W}\right) x_i x_j}}. \tag{17}$$

where $s_i^+ = \sum_j R_{ij}$ and $s_j^- = \sum_j R_{ji}$ denote the in and out strength (i.e. weighted degree) of nodes i and j respectively, R_{ij} is the weighted adjacency matrix, W the sum of edge strength, and δ_{ij} the Kronecker delta that is 1 if $i = j$ and 0 otherwise. For the unweighted and undirected case we have $s_i^+ = s_i^- = k_i$, the degree of node i, and we recover the standard assortativity coefficient from Newman (2018):

$$\rho_x' = \frac{\sum_{ij}\left(R_{ij} - \frac{k_i k_j}{W}\right) x_i x_j}{\sum_{ij}\left(k_i \delta_{ij} - \frac{k_i k_j}{W}\right) x_i x_j}. \tag{18}$$

For Table 1, we calculate $\rho_{\sum_{t=2021}^{2034} o_t}$ and $\rho_{\sum_{t=2035}^{2038} o_t}$ using Eq. (17).

Weighted categorical assortativity The categorical assortativity values in Table 1 are calculated with a weighted variety of Eq. 2 in Newman (2003). In Newman's notation, categorical assortativity is

$$r = \frac{\sum_i e_{ii} - \sum_i d_i b_i}{1 - \sum_i d_i b_i}, \tag{19}$$

with $d_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$, where e_{ij} is the fraction of all edges that connect a node of type i to a node of type j (Newman, 2003). In our application, with weighted networks, we use Eq. (19) to calculate r but define e_{ij} as the fraction of edge *weights* in the occupational network that connects a node of type i to one of type j, such that

$$e_{ij} = \frac{\sum_{k\in i, l\in j} R_{kl}}{\sum_{kl} R_{kl}}; \tag{20}$$

e_{ij} can be interpreted as the probability that any given occupational transition happened between occupation archetypes i and j. In our application, the types are the occupational groups Temporary growth, Consistent growth, Consistent decline, and all other occupations.

Randomization robustness We run Monte Carlo simulations with randomized shocks to understand the robustness of our estimates. For each value of assortativity we measure, we run 100,000 additional calculations where we keep the nodes and edges fixed but randomize the demand shocks over the nodes. We highlight results that are greater in absolute value than 99.9% with a dagger (†) in the main text, or, in SM Section D.4.3, with one, two, or three stars if the assortativity value is larger than 95%, 99%, or 99.9% of the reshuffled values, respectively.

Node-specific frictions Assortativity is a network-wide measure and might not be informative on individual occupations. For occupation i, it matters what happens in its direct neighbourhood $\mathcal{N}_i = \{j | R_{ij} > 0\}$. We call all jobs in the neighborhood occupations of i the pool of i.

Node-specific frictions arise when the pool of i and i itself are affected in the same way. This borrows from the logic of assortativity. The change in demand in the pool of i at time t is

$$\Delta o_{\mathcal{N}_i,t} = \sum_{jin\mathcal{N}_i} \Delta o_{j,t}. \tag{21}$$

The neighborhood friction $q_{i,t}$ of occupation i is then the weighted average of neighboring occupations demand change:

$$q_i = \frac{\Delta o_{\mathcal{N}_i,t}}{o_{\mathcal{N}_i,t}}. \tag{22}$$

We define two types of node-specific frictions: employer (labor demand) frictions and worker (labor supply) frictions. If both occupation i and its pool experience an increase in demand, it may be hard to find workers to fill all vacancies in i. We call this employer frictions, which can arise even if the pool of i increases but at a slower rate than the demand for i decreases. Vice versa, if occupation i and its pool experience a fall in demand, it may be difficult for workers in i to find a new job. We call this worker frictions.

Sensitivity analysis and robustness of results

We perform a sensitivity analysis on nine assumptions and data sources. For more details, see the sensitivity analysis results in SM Section D.6. For each sensitivity analysis, we reproduce Fig. 2b in Fig. S19. In Fig. S20a and S20b we, plot the cumulative worker demand at the peak (2034) and in the new steady state (2045) respectively. In Fig. S21, we reproduce part of Table 1 and plot the assortativity in the scale-up and scale-down phase for the different assumptions. For each of the assumptions, we also reference which section of the SM discusses the default options.

We probe the following assumptions in our sensitivity analysis:

1. We have assumed (see SM Section B.5) that the input-output network structure does not change in time, i.e., $a_{ij,t} = a_{ij}$. Our sensitivity analysis shows that our results are highly robust with respect to changing this assumption.

2. The capex cost vectors translate how the capital expenditure per electricity technology from the scenario is spent on specific industries in the IO table (see Section C.3). We add noise to the capex cost vectors and find the results robust.

3. The opex literature weights translate how intermediate costs are spent on industries in the IO table. These are used to disaggregate the energy sector in the IO table (see Section C.3). We add noise to the opex cost vectors and find the results robust.

4. The transmission and distribution (T&D) grid line cost are calculated in Section B.2 following the methodology in Way et al. (2022). We test the sensitivity of some parameters and find that these parameters can have a large influence on the results.

5. To remove overly erratic results, we apply a 3-year smoothing window to the energy scenario costs. We also present results without smoothing and with a 5-year smoothing window.

6. We take the employment per occupation-industry pair from BLS and use it to calculate the labor requirements per industry and occupation (see Section A.3). BLS publishes error bars together with the point estimates that we use. We find that our results are robust against using values that are on the extremes of the error bars.

7. We assume unit costs for electricity technologies can change over time according to the ATB cost curves as mentioned in Section C.1. Our default assumption is to use the moderate cost development for each technology. We find that using advanced or conservative cost curves can have a significant impact on the results.

8. We assume exports per sector remain constant over time, and that the direct import fraction (m_j in Eq.(9)) is fixed. We test the sensitivity of these assumptions by using other, stylized projections for direct imports and exports of solar and wind electricity generation products. Specifically, we include four additional scenarios: decreasing direct imports, increasing direct imports, increas-

ing exports, and combined decreasing direct imports and increasing exports. We find that these changes to our trade and competitiveness assumptions can have a strong impact on the results, especially the net worker demand in the decarbonized steady-state phase.

9. We test the sensitivity of the construction sector granularity by using more detailed data on *Power and Communication Line and Related Structures Construction* for the construction part of T&D capex in the B matrix of Eq. (23). Our results are robust to this modification.

We also do a robustness check of the assortativity values in SM Section D.4.3 for different network types: the original relatedness network, a network of empirical occupational mobility between 2011 and 2019, and a combination of the two. Fig. S21 shows the assortativity coefficient values for the scale-up and scale-down phase for all tested scenarios in the sensitivity analysis.

Resource availability

Lead Contact

Correspondence and requests for resources should be addressed to joris.bucker@seh.ox.ac.uk.

Materials availability

This study did not generate any new materials.

Data and Code Availability

We used data from a wide range of sources. Almost all were free and openly available on the internet, but some were accessed via personal correspondence with data providers. For more details, see Supplemental Experimental Procedures Section A. All data will be made available upon request (unless legal restrictions exist).

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Author contributions

Conceptualization, J.B.; methodology, J.B., A.P. and R.M.dR.C.; software, J.B., A.P., R.M.dR.C, and M.C.I.; investigation, J.B. and R.M.dR.C.; data curation, J.B., A.P. and R.M.dR.C.; formal analysis, J.B. and R.M.dR.C; writing—original draft, J.B. and M.C.I.; writing—review & editing, J.B., M.C.I., A.P., R.M.dR.C, and J.D.F.; visualization, J.B., R.M.dR.C, and A.P.; supervision, M.C.I. and J.D.F.; funding acquisition, M.C.I. and J.D.F.

Declaration of interests

The authors declare no competing interests.

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Supplemental Experimental Procedures

Contents

A Data

This section discusses the datasets we use in this study. All datasets we use are publicly accessible. We begin with the data on power system scenarios, followed by the supply chain (input-output) data. We then discuss the occupational employment data and the occupational network data. This section is split according to the same four steps as the Experimental procedures section in the main text.

A.1 Step 1: Energy and cost scenarios

For our analysis we use the NREL's Standard Scenarios[13] which is a widely used set of scenarios based on the US power system capacity expansion models ReEDS (Ho et al., 2021) and dGen (Sigrin et al., 2016). Broadly speaking, these models take the decarbonization pathway as given and calculate the power capacities and generated electricity for each technology, obtained via cost minimization. In particular, we focus on two specific scenarios of the main national-level results of the 2021 Standard Scenarios Report (Cole et al., 2021): 1) *No New Policy* and 2) *95% by 2035*. The *No New Policy* scenario assumes no new carbon reduction policies beyond those in place as of June 2021. The *95% by 2035* scenario assumes a 95%-decrease in CO_2e emissions in 2035 compared to 2005, resulting in a reduction from 1750 Mt CO_2e in 2021 to less than 250 Mt CO_2e by 2035. We show the emission pathways in Fig. S1.

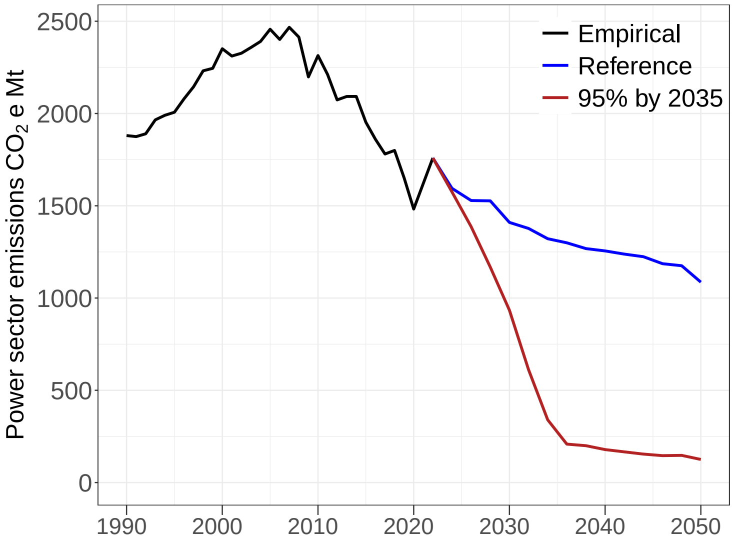

Figure S1: **Annual US power sector emissions in MT of CO_2e.** The black line shows historical power emissions (EPA, 2022), and the blue and red lines estimated emissions based on the scenarios.

To fit with the rest of the analysis, we aggregate the generation and capacity data to eight electricity generation technologies, plus battery storage and transmission and distribution (T&D). The electricity capacity and generation mix scenarios are

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[13] `https://www.nrel.gov/analysis/standard-scenarios.html`

shown in the main text in Fig. 1, and the transmission lines capacity are depicted in Figure S2. In the fast decarbonization scenario, transmission lines are required to expand faster in TW-miles than in the reference scenario.

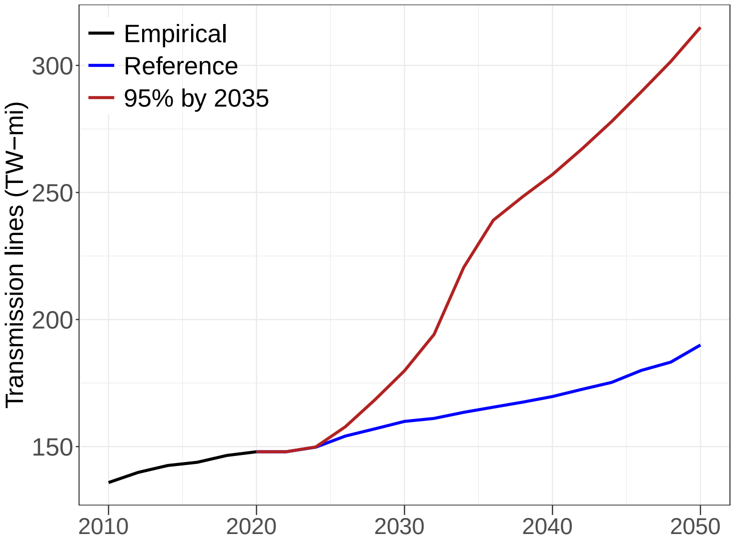

Figure S2: **Transmission lines in MW-mile through time.** Data until 2020 represents historical data; data after 2020 are scenario-specific.

The decarbonization pathways rely heavily on solar and wind. Nuclear and hydro are maintained roughly at their current levels. Coal is phased out, as well as a large portion of natural gas generation, although gas capacity remains fairly constant. Bioenergy and geothermal electricity generation remain small throughout. New generation capacity to deal with growing energy demand also comes from wind and solar, due to their lower cost. The decarbonization scenario manages the increased levels of renewable intermittency from renewables in three ways: increased (battery) storage, a relatively high level of natural gas capacity compared to natural gas electricity generation, and grid expansion.

In the *no-new-policy reference* scenario, coal electricity capacity and generation drop – albeit slowly – but natural gas grows over time. The share of renewables also grows, due to their lower cost and policies in place before June 2021.

Technology-specific cost projections and capacity factors are based on NREL's

Annual Technology Database (ATB).[14] The cost data are broken down into capital expenditures (capex), fixed and variable operational expenditures and fuel costs (opex).[15] Data on unit costs, power capacities, generation and retirement, as well as the input-output data, all use different technology aggregation levels. More details on how we harmonize these can be found in Section C.1. See Section D.6 for more information on the sensitivity analysis of the unit cost projections.

The scenarios considered here assume exogenous unit cost projections, although it has been pointed out that energy technology costs develop endogenously, depending on overall deployment (Way et al., 2022). We test the impact of more advanced or conservative cost assumptions in Section D.6 but leave a more thorough examination of the effects of endogenous price mechanisms on the labor market for future research.

A.2 Step 2: Input-output model

To estimate the direct and upstream supply chain effects of the changes in electricity technology capex and opex, we use the 2018 US data published by the Bureau of Economic Analysis to construct domestic input-output (IO) tables (Bureau of Economic Analysis, 2022b). We remove any imports from the IO table, so that our results only point to US jobs. Vice versa, we assume exports are not affected by the scenarios and remain constant in absolute value. We use the 2018 data to have an estimate of a relatively stable economic situation before the COVID pandemic.[16] See Section B.5 on how we calculate domestic IO tables. We show in Section D.6 that our results are highly robust when using IO tables from different years. We also show in Section D.6 the sensitivity of our results to alternative, stylized import

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[14] `https://atb.nrel.gov/`

[15] The 2021 ATB gives cost in 2019-USD, which we further deflate to 2018-USD using BEA's GDP deflator (which was 1.8% for 2018-2019: `https://www.bea.gov/data/prices-inflation/gdp-price-deflator`). Coal and gas fuel cost were absent in the 2021 ATB, so we use the cost estimates from the 2020 ATB, which were already in 2018-USD.

[16] We use 2018 rather than 2019 to leverage the fact that BLS has not yet updated its occupational classification, allowing us a direct comparison with earlier years.

and export assumptions.

The relevant electricity generation technologies are not separate industries in the official IO tables but are bundled together in the *Utilities* sector. We manually disaggregate the Utilities sector into nine electricity generation sectors.[17] We do this partially using the 2012 detailed IO table and partially using literature estimates of the opex cost structure of different electricity technologies. We use additional literature estimates for translating capex changes to final demand shocks. See Section B.6 on our disaggregation approach, Section C.4 for the data used, and Section D.6 for a sensitivity analysis on the literature estimates. Electricity generation outside of the Utilities sector is out of scope, as discussed in Section C.5.

There are alternatives available to the national IO tables that already include several electricity generation technologies, such as the multi-regional IO tables (MRIOs) EXIOBASE and GTAP (Stadler et al., 2018; Aguiar et al., 2023). We chose to work with the national tables for two reasons: 1) the employment data we use from the Bureau of Labor Statistics (BLS) is a natural fit for the BEA data, and 2) The BEA tables are the standard for the US, forming the basis for the US tables of EXIOBASE and GTAP. Those MRIOs are designed for global supply chain analysis, and require further statistical fitting to make the countries' imports and exports align. MRIOs also require the additional effort of combining and disaggregating industries to create a uniform dataset.

A.3 Step 3: Modelling occupational demand impacts

We use data from the US Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) database (Bureau of Labor Statistics, 2021) to create the industry-occupation matrix B where element B_{ij} is the number of workers of occupation i working in industry j, and $\sum_{ij} B_{ij} = 145$ million, the total size of the US employed labor force in 2018. This is also sometimes called the manpower

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[17] This contains one *Other electricity generation* sector, which we assume to be zero in NREL's scenario.

matrix (e.g. Bezdek, 1973). BLS industry codes are slightly different from BEA industry codes. We manually impute industry-occupation data that is censored in the published tables. We harmonize the datasets using a crosswalk provided by the U.S. Environmental Protection Agency (EPA) (Environmental Protection Agency, 2022). See Section C.7 for more details on the imputation and data harmonization. We use BLS's standard errors on their estimates for a sensitivity analysis on matrix B in Section D.6

Combining B with industry output data x allows us to calculate M_{ij}, the number of workers from occupation i employed in industry j per dollar of output as

$$M_{ij} = \frac{B_{ij}}{x_j}, \tag{23}$$

where x_j is the total output of industry j in 2018-USD.

A.3.1 Occupations

We divide all workers into 539 occupations. We use 2010 SOC codes, which BLS uses for its annual OEWS surveys between 2010 and 2018. This data is available at four aggregation levels: major (22 occupations in the 2018 OEWS), minor (93), broad (455), and detailed (809). To generate the results shown in Fig. 4b, we further define eleven high level occupational categories.[18]

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[18] The 11 occupational categories are based on the 22 major BLS occupations as follows: Healthcare contains *Healthcare Practitioners and Technical Occupations* and *Healthcare Support Occupations*; Engineering and IT contains *Computer and Mathematical Occupations* and *Architecture and Engineering Occupations*; Production occupations contains *Production occupations*; Life, physical, and social science contains *Life, Physical, and Social Science Occupations*; Education, social services, and media contains *Arts, Design, Entertainment, Sports, and Media Occupations*, *Education, Training, and Library Occupations*, and *Community and Social Service Occupations*; Construction and extraction contains *Construction and Extraction Occupations* and *Farming, Fishing, and Forestry Occupations*; Transportation contains *Transportation and Material Moving Occupations*; Installation and maintenance contains *Installation, Maintenance, and Repair Occupations* and *Building and Grounds Cleaning and Maintenance Occupations*; Other service occupations contains *Personal Care and Service Occupations*, *Food Preparation and Serving Related Occupations*, and *Protective Service Occupations*; Management and financial includes *Management Occupations*, *Business and Financial Operations Occupations*, and *Legal Occupations*, and Sales and administrative support contains *Office and Administrative Support Occupations* and *Sales and Related Occupations*

Our list of occupations is a combination of broad and detailed occupation categories, generated using the most detailed one-to-one harmonization possible with *OCC* codes, which is a different classification used by the US Census Bureau.

As a starting point, we take the list of occupations from a US Census Bureau harmonization table of Census *OCC* codes with 2010 SOC codes.[19] We limit ourselves to the codes available in BLS (i.e., excluding military occupations). For more details on the exact mapping between the two datasets, see Section C.8.

A.3.2 Skill data

Data on occupational skills is taken from O*NET 25.0 Data Dictionary.[20] See Consoli et al. (2016) for details.

A.4 Step 4: Occupational network and frictions

We use two datasets on the relatedness between occupations: O*NET's data on related occupations,[21] and an empirical occupational mobility network based on US Census Bureau data from IPUMS, following Vom Lehn et al. (2022). We only use the latter to impute missing data in the related occupation network, as explained below, and for robustness testing. For a further discussion on the different occupational networks, see Section B.9.

The Related Occupations network is created using O*NET's lists of related occupations, following Bowen et al. (2018). For each occupation, O*NET lists twenty occupations it is related to. In previous versions of O*NET, this data was called the *career changers matrix*.

Not all occupations are covered by the related occupation network. Occupations whose name contains 'All other' (e.g., *Sales and Related Workers, All Other'*), or

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[19] https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

[20] https://www.onetcenter.org/dictionary/25.0/excel

[21] https://www.onetcenter.org/dictionary/26.3/excel/related_occupations.html

'Miscellaneous' tags (e.g., *'Miscellaneous Financial Clerks'*), are often missing because they are deemed too general. Instead, we impute links for these occupations from the occupational mobility network of observed past mobility.

B Supplemental Methods

B.1 Improvement potential of proposed methodology

Our IO model has a few important limitations that are beyond the scope of our research to address. Our results are aggregated to 82 industries and 539 occupations, but differences between firms in the same industry (Diem et al., 2024) or variation between jobs in the same occupation (Saussay et al., 2022; Caunedo et al., 2023; Atalay et al., 2020) can be obfuscated by our level of aggregation. For example, we did not separate metal mining from coal mining.[22]

As mentioned before, changes in labor demand and their associated wages and how differently workers spend them do not feed back into final demand in our model specification. Our results therefore include direct and indirect upstream supply chain jobs, but not *induced* jobs. Induced jobs are created when increased employment or higher wages lead to more spending by workers, which in turn further increases economic demand, creating more jobs. Stavropoulos and Burger (2020) argue that studies that include induced jobs often report lower overall job growth for the energy transition.

Also out of scope for this research effort are the capital goods used in the electricity capex supply chains that are not part of the final electricity mix. For example, the operation of oil platforms, pipelines, and oil tankers is part of the analysis, but not the construction of these secondary capital goods. I.e., workers on the opex side of these operations (oil rig staff, pipeline controllers, and oil tanker sailors) are

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[22] The mining industry will undergo an eventual decline during the transition due to lower fossil fuel use, but it will receive a boost in our analysis from increased demand for the materials that are required for clean energy technologies sourced within the US.

part of this analysis, but not the welders on the shipyards, or the ground clearance construction worker for a pipeline project. This is a consequence of the exclusion of capex in IO tables and national accounts data, and may underestimate the total job estimates in this study (Södersten and Lenzen, 2020).

Additionally, out of scope for this research are both opex and capex impacts from transition related projects outside the electricity sector, such as in automotive (e.g. batteries for electric vehicles), or heating (e.g. heat pump installation or other building climate control equipment).

As mentioned in the introduction, our study also disregards geographical effects. In previous studies, these have been taken into account by disaggregating Input-Output tables (e.g., Kahouli and Martin, 2018), or by using firm level supply chain data (e.g., Carvalho et al., 2021). Our model also leaves out the effect of potential wage changes, including the *green premium* (for a discussion on the green wage premium, see, e.g., Antoni et al., 2015; Saussay et al., 2022), and changes beyond the power sector. We also assume an unchanged economic structure and policy landscape, where only the electricity mix changes. Changing effects and policies regarding manufacturing on-shoring, automation, and aging will undoubtedly impact the results of our analysis, either directly (e.g., more wind turbine components are manufactured domestically), or indirectly (e.g., aging will require more health care staff), which potentially changes the skill mismatch frictions in the labor market. Automation, in particular, could generate important changes to labor markets and the nature of work (see, e.g., Acemoglu and Restrepo, 2019; Frey and Osborne, 2017). All such changes can exacerbate or reduce the direct and indirect impacts presented in this study. Further research into how all aspects of a fast green transition can best be managed while minimizing disruptions to the labor market might be worthwhile. The methods we have employed here are sufficiently general that they could be applied to such analyses or virtually any mix of labor transforming trends, in the US and elsewhere.

B.2 Transmission and Distribution cost calculation

NREL reports transmission line capacity T_t (in MW-mile) in year t, but not their associated capex or opex costs. We follow the methodology of Way et al. (2022) for transforming MW-mi into capex, and assume opex scales linearly with the total deployed equipment capital new-value. Way et al. (2022) assume that additional electricity distribution requirements can partially be met by increasing the capacity of lines on existing grid infrastructure. As the grid requires more capacity, we assume old grid infrastructure is replaced with lines that carry three times the capacity of the old ones, for 1.37 times the capex of *standard* transmission line cost. That means that for every 100 MW-mi of grid expansion, 50 miles of the existing grid is replaced with lines that are three times as powerful (see p. 44 supplemental Experimental Procedures of Way et al., 2022). Unit costs used in our study are based on an NREL study showing average transmission line project costs of 1,384 USD (Jorgensen et al., 2017, Table 4) (1,433 2018-USD).[23]

We include changes to both the transmission and distribution grid (T&D), although NREL does not model the latter. We follow Way et al. (2022) by inferring from IEA data that between 2010–2019 about 69% of all US grid investments were on distribution grids, while 31% were on transmission grids (IEA, 2022). Since this 69/31 ratio remained fairly stable in the 2010s, we assume the same investment ratio for the future.

Thus, grid capex spending is given by:

$$C^{\text{capex}}_{\text{T\&D},t} = T_t/2 \times 1.37 \times 1433 \times (100/31), \tag{24}$$

where T_t is the amount of new transmission capacity in MW-mi, $T_t/2$ the number of miles of old transmission grid that are upgraded, $T_t/2 \times 1.37 \times 1433$ the cost of upgrading to three times as powerful lines in 2018-USD, and (100/31) the factor

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[23] We use the BEA price index for private fixed investment in power and communication structures (T50304).

to account for the distribution grid too. As with the generation technologies, we smooth the capex spending using a 3-year rolling window.

Similarly, we assume opex scales with the new-cost of the transmission grid capital stock, in particular

$$C^{\text{opex}}_{\text{T\&D},t} = C^{\text{fix opex}}_{\text{T\&D},t} \propto 1.00 \times (T_0 - (T_t - T_0)/2) + 1.37 \times (T_t - T_0)/2, \tag{25}$$

where the first part relates to the old part of the grid, and the second to the new upgraded part. We assume T&D's variable costs to be zero: $C^{\text{var opex}}_{\text{T\&D},t} = 0$.

In Section D.6, we test the sensitivity of our results with respect to the unit cost assumption, as well as the 1.37 factors for capex and opex, and find that T&D cost uncertainties to be one of the largest sources of uncertainty in our analysis.

B.3 Battery cost

We cannot include battery storage as a technology in our IO table using the proposed methodology, because it is not part of the electricity sector NAICS 2211. In fact, there is not a NAICS code (yet) for grid-scale battery storage facilities. We add battery storage opex workers to our results via *capex*, following the final demand approach as laid out in Blair and Miller (2009) (see Section B.4). We assume all battery storage opex is fixed and represents maintenance and replacement costs. We assume the spending breakdown of battery storage opex is the same as used for battery storage capex. We justify this on two battery cost breakdown analyses, which report that battery opex work is often mainly replacement maintenance that has a similar breakdown to newly manufactured and installed capex (Feldman et al., 2021; Black & Veatch, 2012). Instead of Eq. (5), we calculate

$$C^{\text{capex}}_{\text{battery},t} = C^{\text{pure capex}}_{\text{battery},t} + C^{\text{fix opex}}_{\text{battery},t}, \tag{26}$$

where $C_{\text{battery},t}^{\text{fix opex}}$ follows Eq. (1), and

$$C_{\text{battery},t}^{\text{pure capex}} = \max\left\{\left(Y_{\text{battery},t} - Y_{\text{battery},t-1} + R_{\text{battery},t-1}\right), 0\right\} c_{\text{battery},t}^{\text{capex}} \tag{27}$$

is similar to Eq. (5), and $C_{\text{battery},t}^{\text{var opex}} = C_{\text{battery},t}^{\text{fuel}} = 0$.

B.4 Differentiation between capex and opex

In our methodology we treat opex and capex costs separately, despite the overhead this creates. We do this for three reasons. Firstly, fossil fuel technologies and renewables have very different cost structures: renewables often require more capex and less opex. Secondly, the distinction between the two costs matters for workers. Opex employment is generally stable and required for the duration of electricity generation. Capex work is often only available before electricity generation can start (and later during capital goods replacement). Their occupational profiles are different too.

Thirdly, input-output frameworks naturally treat opex and capex differently. Capex mutations can be modeled as a change in investment, a final demand category. Opex mutations require a modification of the intermediate expenses matrix. Blair and Miller (2009) indicate two potential routes for dealing with new industries that are not yet encapsulated in the IO data: A complete inclusion in the technical coefficient matrix (p. 636), or the final-demand approach (p. 634). The final-demand approach has the advantage of requiring fewer data inputs. A disadvantage is that only backward upstream links are included, and no downstream effects. A further caveat is that most of the electricity generation sectors are not completely *new*, as these operational expenses (opex) are partly already included in the existing *Utilities* sector. For these reasons, we decided to follow the final-demand approach for capex, and for opex we split the utility sector in the IO table into several electricity generation technologies. The exception is battery storage opex, for which we follow the final demand approach, as was explained in Section B.3.

B.5 Domestic input-output tables

This section provides an explanation of how we calculated the domestic production network matrix A. Matrix A is calculated using US domestic make and use tables from BEA at the summary (71 industries/commodities) level. Elements a_{ij} represent the value of goods from domestic industry i required to produce one dollar output for industry j.

We derive the domestic IO table A and domestic final demand vector f, which we use in Eq. (6), following the official BEA derivation calculations,[24] and proceed as follows:

Make and use tables The symmetric *use* matrix U has elements U_{ij}, the value in USD in 2018 used of commodity i in the production of industry j. The *make* matrix V has elements V_{ij}, the value in USD in 2018 created of commodity i by industry j. Let W be the part of U that is imported, with W_{ij} the value in USD of commodity i that is imported for the production of industry j. The vector g is the total industry output for the US (g_i is the 2018 USD output of industry i), and q is the total commodity output. The total amount of imports used in industry j is $w_j = \sum_i W_{ij}$.

Scrap and noncomparable imports In addition to the commodities associated with its 71 industries, the BEA data contains two more commodities, *Scrap, used, and secondhand products* h, and *Noncomparable imports and rest-of-the-world adjustment* i. For both we have three vectors (use, make and import per industry), respectively h^u, h^v and h^w, and i^u, i^v, and i^w. We add the noncompareable imports

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[24] (See chapter 12 of the BEA IO manual https://www.bea.gov/sites/default/files/methodologies/IOmanual_092906.pdf) as well as the domestic requirements derivation as per https://apps.bea.gov/scb/pdf/2017/03%20March/0317_introducing_domestic_requirement_tables.pdf

to the total amount of imports per industry $\tilde{w}$ with elements $\tilde{w}_j = w_j + (i^u_j - i^w_j)$.

Market share matrix The same commodity can be produced by different industries. The *market share* matrix $D = V\hat{q}^{-1}$ has elements D_{ij} that give the share of industry i in producing commodity j, where $\hat{q}$ indicated a diagonal matrix with the elements of vector q along the diagonal.

Next, we adjust the market share matrix for scrap. Let p be the industry scrap adjustment vector with elements $p_i = g_i/(g_i - h^v_i)$, which is larger than 1 if industry i produces scrap. The adjusted market share matrix $\tilde{D}$ leaves out scrap; each element $\tilde{D}_{ij}$ gives the market share of industry i in commodity j, excluding scrap production, as $\tilde{D}_{ij} = p_i D_{ij}$.

Domestic industry by industry spending and recipe matrices The domestic industry-by-industry matrix $\tilde{Z}$ can be found by multiplying the domestic use matrix $\tilde{U} = U - W$[25] with the market share matrix

$$\tilde{Z} = \tilde{D}\tilde{U}. \tag{28}$$

In the final step, we add a row with total imports to get the domestic production network including imports

$$Z = [\tilde{Z}; \tilde{w}]. \tag{29}$$

Thus, finally, the domestic IO table is

$$A = Z\hat{g}^{-1}. \tag{30}$$

Domestic final demand The domestic final demand follows analogously. Let F_c be the final commodity demand matrix, with $F_{c,ij}$ the final demand in 2018-USD for commodity i by final demand category j. Different categories of final demand

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[25] To maintain the same total amount of use in the absence of scrap, we inflate the columns of $\tilde{U}$ proportionally with the amount spent on scrap by each industry.

can include *household spending*, *government spending*, and *exports*. Let F_c^W be the final demand that is spent abroad, and $\tilde{F}_c = F_c - F_c^W$ the domestic final demand per commodity (including exports). The domestic final demand per industry F with F_{ij} the final demand in 2018-USD for goods from industry i by final demand category j is then

$$F = \tilde{D}\tilde{F}_c. \tag{31}$$

We can sum over the categories to find the total domestic final demand vector f with elements $f_i = \sum_c F_{ic}$ of domestic final demand for industry i.

B.6 Electricity sector disaggregation in the US IO tables

In order to model the power sector transition, we disaggregate the generic utility sector in the IO matrix A, as calculated in Eq. (30), into different electricity generation sectors and other utilities. This requires additional input from BEA's 2012 detailed (389 industries) US IO table and literature estimates on production inputs (see Section C.3). We also use BEA data on detailed industry output in 2018, which includes several electricity generation sectors. We do not include battery electricity storage as it has not been part of the BEA utility industry. We add it via the final demand approach as explained in Section B.3.

While we add different electricity generation sectors in our IO matrix, the IO table totals must remain internally consistent. We use a bi-proportional method-based technique to ensure this. Blair and Miller (2009, sect 7.4.7) discuss this method in the context of projecting IO tables forward in time when only aggregate data was available. Our problem can be dealt with in a similar fashion. But rather than an outdated matrix, we use literature estimates of disaggregated sectors.

This section lays out the IO table disaggregation procedure, and Section C.4 then demonstrates how we apply it to the US utility sector.

B.6.1 IO industry disaggregation procedure

Recall the IO matrix A represents the production network. We call the i^{th} columns of A the production recipe of industry i. The j^{th} row of A shows the fraction of spending of other industries on industry i. We call these rows output recipes.

New industries Let A^* be the IO matrix with industry i disaggregated into m sub-industries $(i_1, \ldots, i_m)$, with element $A^*_{i_k,j}$ the amount of industry i_k's goods required to produce one 2018-USD of output of industry j, with $k \leq m; j \leq n$. The output of sub-industry i_k as a fraction of i's total output w_k such that $\sum_k w_k = 1$.

Following Lindner et al. (2012),[26] the subsequent constraints need to be satisfied:

a) The sub-industries' production recipes should sum to the original production recipe:

$$\sum_{k=1}^{m} w_k a^*_{ji_k} = a_{ji} \quad \forall j \tag{32}$$

b) The output recipes of the sub-industries should sum to the output recipe of industry i:

$$\sum_{k=1}^{m} a^*_{i_k j} = a_{ij} \quad \forall j \tag{33}$$

c) Any intermediate flows between the sub-industries should sum to the self-link of the original industry:

$$\sum_{k=1}^{m} \sum_{k'=1}^{m} w_k a^*_{i_k i'_k} = a_{ii} \tag{34}$$

In addition, we require the following two regularization constraints to hold:

d) All items of A^* should be non-negative: $a^*_{ij} \geq 0$

e) Total output should equal intermediate spending plus value added. The production recipes should sum to $\sum_j a^*_{i,j} = \alpha_i \leq 1$, where $\alpha_i + \beta_i = 1$ with $\beta_i = \frac{\text{value added}_i}{x_i}$ the fraction of value added of output of industry i.

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[26] Equations 6-8

Let us assume that we have an approximation of the production recipes D of the m sub-industries of industry i where element $d_{j,k}; k \leq m, j \leq n$ is the approximation of the value of goods required from industry j for one dollar of output of sub-industry k. While the approximate recipes could be imputed directly in A to create A^*, they are unlikely to satisfy the aforementioned constraints.

We use an iterative bi-proportional fitting method that fits the initial estimates in the larger table such that it respects the aforementioned constraints.

Iterative proportional fitting procedure We use bi-proportional fitting, also known as the 'RAS method', as a heuristic to find a matrix D^* which is closest to an initial matrix D but has the row and column total of a target matrix A (Blair and Miller, 2009; Stephan, 1942). Matrix D^* is then used as a proxy for A, whose interior is unknown. The fitted matrix is of the form $D^* = PDQ$ where P and Q are diagonal matrices.

Most algorithms to find D^* are iterative, adjusting P and Q successively until convergence, called iterative proportional fitting (IPF).

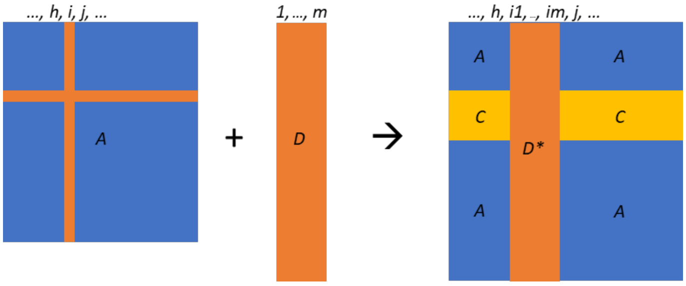

Figure S3: **Iterative proportional fitting procedure (IPFP).** Production network matrix A on the left, the new recipes matrix D in the middle, and the new production network matrix A^* with industry i disaggregated into m sub-industries on the right

Our IO disaggregation procedure has the following steps (see also Fig. S3):

1. We identify the production recipes $1, \ldots, m$ that will take the place of the original production recipe i (matrix D in Fig. S3)

2. We insert a set of new output recipes $i_1, \ldots, i_m$ by splitting the original output recipe i; we split it proportional to the fraction of output attributed to each

of the sub-industries $1, \dots, m$. This refers to area C in Fig. S3 and satisfies constraints *b, d* and *e* above for the non-disaggregated industries. We assume that all industries are agnostic about the source of electricity, and consume electricity as per the average grid mix.

3. We apply IPF to fit the new recipes in D with two constraints: The columns sum to the fraction of output that we attribute to intermediate demand (constraint *e* above), while the rows sum to the original production recipe (constraint *a* above). We then replace production recipe i with these new values. This refers to area D^* in Fig. S3. The new production recipes of the disaggregated industries now satisfy constraints *a, d* and *e* above, and the self-links satisfy constraint *c*.

4. We combine the new production recipes, output recipes and self-links with the original input-output matrix to create the new input-output matrix.

B.7 Occupational typology

In this section, we formalize the definition of occupational typology, and present an alternative method for robustness checks. We classify occupations into four types according to their demand dynamics in the scale-up and scale-down phases (see Fig. 3).

Occupation i has a change of demand between 2020 and 2034 of $\dot{o}_i^{\text{up}} = (\sum_{t=2021}^{t=2034} \Delta o_t)/o_{i,2020}$, and, similarly, $\dot{o}_i^{\text{down}} = (\sum_{t=2035}^{t=2038} \Delta o_{i,t})/o_{i,2020}$. If $\sqrt{(\dot{o}_i^{\text{up}})^2 + (\dot{o}_i^{\text{down}})^2} < 0.01$ we conclude occupation i is not markedly affected. In all other cases, we assign the occupations to the three different types as follows:

$$i \in \text{Consistent growth if } (\dot{o}_i^{\text{up}} > 0) \wedge (\dot{o}_i^{\text{down}} > 0) \tag{35}$$

$$i \in \text{Temporary growth if } (\dot{o}_i^{\text{up}} > 0) \wedge (\dot{o}_i^{\text{down}} < 0) \tag{36}$$

$$i \in \text{Consistent decline if } (\dot{o}_i^{\text{up}} < 0) \wedge (\dot{o}_i^{\text{down}} < 0), \tag{37}$$

Alternative typology definition Our alternative definition is based on the idea that all occupations can be part of multiple 'occupation types' to a certain degree, depending on how the actual values of demand increase and decrease over all industries in which workers are employed in that occupation. We will say that a fraction of jobs in a particular occupation can be part of type α, and a second fraction to type β, etc. Let us define the following quantities for occupation i, which calculate the total positive impact $o_{i,+}$ and total negative impact $o_{i,-}$ on demand for occupation i through the scenario between 2020 and 2050:

$$o_{i,+} = \sum_{t=2021}^{t=2050} M_{ij} \max(0, \Delta x_{t,j}), \tag{38}$$

and

$$o_{i,+} = -\sum_{t=2021}^{t=2050} M_{ij} \min(0, \Delta x_{t,j}), \tag{39}$$

where $\Delta x_{t,j}$ is the change in industry j's output in year t, and M_{ij} the number of workers in occupation i per USD-2018 output of industry j.

The number of *Consistent Growth* jobs in occupation i is

$$o_{i,\text{perm}} = \max(0, o_{i,+} - o_{i,-}). \tag{40}$$

Jobs classified as *Consistent Decline* are jobs that are lost in shrinking industries that did not recover. The number of *Consistent Decline* jobs in occupation i is

$$o_{i,\text{decline}} = -\min(0, o_{i,+} - o_{i,-}). \tag{41}$$

Temporary growth jobs are jobs created by industries that are phased out after the transition reaches its zenith. The number of *Temporary growth* jobs in occupation i is

$$o_{i,\text{temp}} = o_{i,+} - o_{i,\text{perm}}. \tag{42}$$

The fraction of occupation i that is part of type α is then $f_i^\alpha = \frac{o_{i,\alpha}}{o_{i,2020}}$. Our alternative, three dimensional, type definition of occupation i is then given by $f_i = (f_i^{\text{perm}}, f_i^{\text{temp}}, f_i^{\text{decline}})$.

B.8 Occupational typology location quotients

The location quotient of occupation i in state β is the occupation i's share in state β's workforce relative to the US as a whole. Specifically, we define

$$\mathrm{LQ}_{i,\beta} = \frac{o_{i,\beta} / \sum_{i \in \text{Occupations}} o_{i,\beta}}{\sum_{\beta \in \text{States}} o_{i,\beta} / \sum_{i \in \text{Occupations}} \sum_{\beta \in \text{States}} o_{i,\beta}} = \frac{o_{i,\beta}/o_\beta}{o_i/o}, \tag{43}$$

with $o_{i,\beta}$ is the total number of workers in occupation i in state β, and o_β the total number of workers in state β, o_i the total number of workers in occupation i, and o the total number of workers in the US. In Fig. S13, we plot the mean location quotient for all occupations per type.

B.9 Occupation network choice

The occupational network reflects the options workers have outside their current occupation. There are different reasons why workers would change their occupation, including skill similarity, wage and career progression considerations, preferences for specific job tasks, location and travel requirements, and perceived status (Nedelkoska et al., 2018; Hollywood, 2002; Schmutte, 2014; Neffke et al., 2024). We therefore considered multiple options for measuring relatedness between occupations. Besides O*NET's relatedness measure, there are empirically observed mobility networks, and networks based on tasks or skills. We will introduce each of these approaches and weigh the pros and cons of our chosen approach against the alternatives.

Relatedness network As explained in the Methodology section, the network we use for the main results is based on O*NET's classification of related occupations (previously known as the *career changers* matrix) and is defined by adjacency matrix R.

Empirical occupational mobility network Empirical occupational mobility networks infer the likelihood of transitioning between occupations from empirical job mobility data, such as census data or surveys. Del Rio-Chanona et al. (2021) construct an occupational mobility network from US census data to inform an agent-based labor market model. Vom Lehn et al. (2022) use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) (Flood et al., 2021) that takes part every year in March. Participants are asked about their current occupation and their occupation the previous year. In this way, the ASEC supplement reduces errors in the estimation of occupational mobility due to misclassification (Cheng and Park, 2020).

Following Vom Lehn et al. (2022), we construct an occupational mobility network for 2010–2019 with adjacency matrix A^{OMN}. Edges in the occupational mobility network are weighted and directed – the weight of an edge from occupation i to j is the average number of workers per year that changed from occupation i to j between 2010 and 2019 (inclusive). We only include occupations that presented transitions between 2010 and 2019. This leads to a strongly connected network with 539 nodes.

Skill-based networks Links between nodes can also be informed by the skill difference between occupations, or other job characteristics, directly. For example, Anderson (2017) pulls skills data off an online work platform and shows which skills lead to higher wages for individual workers. Workers with diverse skills that are in high demand but short supply are especially valuable. Mealy et al. (2018) construct a network where occupations are more strongly connected if they perform the same tasks.

Combined network We define a combined network using both O*NET's Relatedness Occupation data and the empirical occupation transitions data following Vom Lehn et al. (2022). We define the mixed 50/50 network with the adjacency matrix

$$A^{\text{mix50}} = \frac{R + A^{\text{OMN}}}{2}, \tag{44}$$

where R and A^{OMN} are the adjacency matrices defined by O*NET's related occupation list and the empirical occupational mobility network, respectively.

Pros and cons of our approach vs alternatives We chose to present our main results using O*NET's relatedness network because it attempts to capture various reasons for relatedness in one metric, and it is intended to be forward-looking. A relatedness measure that is based on the skill or task difference between occupations captures an important factor that may induce or inhibit a worker from moving into a particular occupation but neglects other aspects of the decision. Mealy et al. (2018) find that task similarity is a significant exploratory variable for empirical occupational mobility, although with a lot of variation left unexplained. This type of relatedness measure may represent an upper limit of mobility: if workers are willing to relocate or take a pay cut in a disruptive situation, their skill set may still inhibit them from getting a job.

Empirical occupational mobility networks have the advantage that they combine all job-switching considerations by measuring occupational mobility directly. A downside is that economic factors of the period in which the data was gathered can influence the results. For example, if the financial sector saw a decline in activity, fewer workers would be observed moving into financial occupations, even if many more would take up such a job were the economic situation different.

A further, more practical limitation of the empirical occupational mobility network is that some occupations that are relevant to the transition have not existed for very long, such as wind turbine technicians and solar panel installers. Indeed, we were only able to observe a handful of transitions in and out of those occupations, which leads to noisy results.

In Experimental procedures and Section A.4, we discuss the occupational network built using O*NET's list of *related* occupations. O*NET's Related Occupation list was constructed using different data sources, including expert opinions, and is meant as a forward looking measure. For this reason, we decided to use this network for our main analysis. A downside is that it is an ad-hoc list that contains some arbitrariness and may not fully reflect reality; for example, each occupation that is included has 20 related occupations, but it is not clear why every occupation should have exactly 20 related occupations.

In the robustness test for assortativity in Section D.4.3, we show that our main results using the relatedness network hold when we use the empirical occupational mobility network or the 50/50 combined network instead.

C Supplemental Data

C.1 Matching of technologies and industries

In our analysis, we combine several large datasets, which comes with the challenge of aligning different definitions of technologies and industries across these datasets. We take the unit costs for various power technologies from NREL's 2021 Annual Technology Baseline (ATB) (NREL, 2021). Technology costs are further separated into capital expenditure, fixed and variable operational expenditure, and fuel costs. Since no fuel costs for gas and coal are reported in the 2021 ATB version, we have used the 2020 ATB costs for these cases. For all technologies, we have used the *moderate* future cost pathways, which are consistent with the power sector scenarios considered here.

As can be seen in Table S1, there is not always a clear one-to-one mapping between the ATB technologies and the capacity and generation technologies from

NREL's Standard Scenarios from (Cole et al., 2021). The cost data tends to be much more granular for most technologies but does not include all technologies that are reported in the Cambium scenarios (e.g., Oil-Gas-Steam or Bioenergy with carbon capture).

ATB Technology	ATB Technology Detail	Cambium technologies	IO
Utility-Scale Battery Storage	4Hr Battery Storage	battery	Batteries
Biopower	Dedicated	beccs	Bio
Biopower	Dedicated	biomass	Bio
Coal_FE	newAvgCF	coal	Coal
NaturalGas_FE	CCAvgCF	gas.cc	Gas
NaturalGas_FE	CCCCSAvgCF	gas.cc.ccs	Gas
NaturalGas_FE	CTAvgCF	gas.ct	Gas
NaturalGas_FE	CTAvgCF	o.g.s	Gas
Geothermal	HydroFlash	geothermal	Geo
Hydropower	NPD1	hydro	Hydro
Nuclear	Nuclear	nuclear	Nuclear
Pumped Storage Hydropower	Class 3	phs	Hydro
CSP	Class3	csp	Solar
ResPV	Class5	distpv	Solar
CommPV	Class5	distpv	Solar
UtilityPV	Class5	upv	Solar
LandbasedWind	Class4	wind.on	Wind
OffShoreWind	Class3	wind.ofs	Wind
-	-	Transmission grid	T&D

Table S1: **Matching technologies across different datasets.** The left column represents the ATB technologies, which are further differentiated into **detailed** categories (second column). We refer to NREL (2021) for further details on these technologies. The third column gives the technological detail of the NREL Cambium Standard Scenarios as they can be downloaded from `https://scenarioviewer.nrel.gov/` (accessed: September 21, 2022). The fourth column shows the input-output energy categories. ATB cost estimates for transmission and distribution (T&D) are not available: see Section B.2 for details on how we deal with that.

Our results in the main text are based on input-output industries where we disaggregate 10 key energy technologies (see Section C.4). We thus have to further aggregate the more granular cost and power system scenario data. The mappings between the technology definitions of the various datasets are described in detail in Table S1. We also used annual capacity retirement data, which we have obtained via personal correspondence with the authors of the Cambium report.

The NREL scenarios include both utility and distributed electricity generation and capacity, but the other data sources (BLS and BEA) only include utility-scale establishments. Contrary to other generation technologies, distributed solar can be a significant contribution to solar electricity total production. We therefore add distributed solar to the solar IO industry as: $a_{\text{solar},i,t} = a_{\text{solar},i,2018} \times \frac{C^{\text{opex}}_{\text{solar util},t}}{C^{\text{opex}}_{\text{solar util},2018}} \times \frac{C^{\text{opex}}_{\text{solar util},t} + C^{\text{opex}}_{\text{solar dist},t}}{C^{\text{opex}}_{\text{solar util},t}}$, and equivalently for $f_{\text{solar},t} = f_{\text{solar},t-1} \times \frac{C^{\text{opex}}_{\text{solar util},t}}{C^{\text{opex}}_{\text{solar util},t-1}} \times \frac{C^{\text{opex}}_{\text{solar util},t} + C^{\text{opex}}_{\text{solar dist},t}}{C^{\text{opex}}_{\text{solar util},t}}$.

C.2 Domestic capex spending

We only include the capex that is spent domestically. As mentioned before, we use the domestic IO tables to restrict our analysis to US domestic employment (including both direct and indirect jobs) for different electricity generation technologies. However, part of the capex cost can be spent abroad directly and thus never enter the domestic IO table. In Eq. (9), we defined m_i as the fraction of goods produced by industry i that are imported rather than sourced domestically. We calculate m_i using the 2018 BEA use and import table (Bureau of Economic Analysis, 2022b). Recall from Section B.5 that the use table U has elements U_{ij} that are the use of commodity i by industry j, and the import part of that is matrix W where W_{ij} is the value of commodity i that is imported by industry j. The market share matrix D has elements D_{ij} that give the share of industry i in producing commodity j.

Industry	Imports for use in other industries, as a percentage of total intermediate demand
Apparel and leather and allied products	69
Electrical equipment, appliances, and components	56
Computer and electronic products	49
...	...
Construction	0
Wholesale trade	0
Management of companies and enterprises	0

Table S2: **The three industries most and least three imported from for domestic production of intermediate goods in 2018.**

The total industry-to-industry spending matrix is $Z^{\text{tot}} = DU$, of which the import part is $Z^{\text{imp}} = DW$. The total fraction m_i of spending on industry i that is imported is then

$$m_i = \frac{\sum_j Z_{ij}^{\text{imp}}}{\sum_j Z_{ij}^{\text{tot}}}. \tag{45}$$

How much is spent on the domestic industry differs per industry. Table S2 shows the top and bottom three industries by import percentage m in 2018 are shown. For example, 66% of goods acquired from the *Electrical equipment, appliances, and component* industry, and about half of those from the *Computer and electronics* industry were imported in 2018. We assume that these fractions remain constant at 2018 levels. However, recent policy discussions and policies, such as the Inflation Reduction Act and CHIPS and Science Act, indicate that the US is keen to produce more of its own demand domestically (The White House, 2022).

Fig. S4 shows how the import fractions of intermediate goods have changed between 1997 and 2019. The use of imported goods from the 315AL (Apparel and leather and allied products) increased from 32% in 1997 to 82% in 2019.

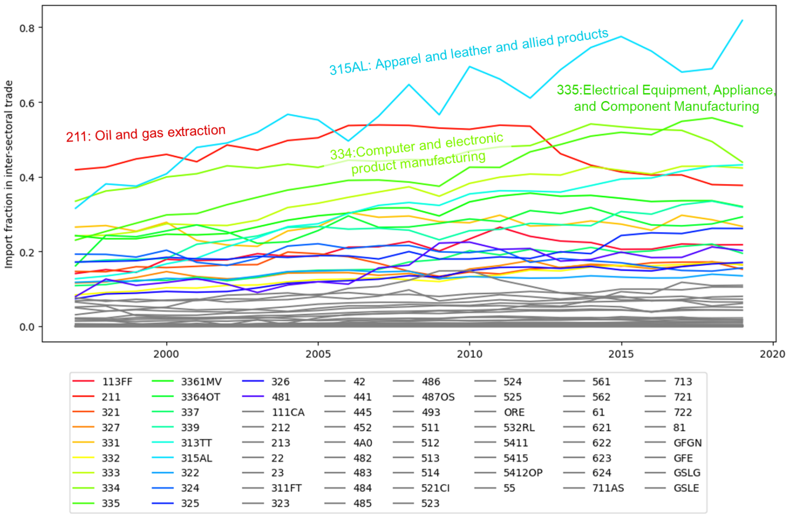

Figure S4: **Intermediate good import fractions over time.** Industries with average import fractions lower than 10% of intermediate trade are colored gray. The top four industries by average import fractions over the entire period are labeled with their full industry names.

More importantly for our analysis, imports of goods from industry 335 (Electrical equipment, appliances, and component manufacturing) and 333 (Machinery) have increased from 23% to 53% and 24% to 42% over the 1997-2019 period, respectively.

The individual time series of Fig. S4 appear to be noisy or exhibit a steady increase. Two industries that show a reversal, from increasing to decreasing imports, are 211 (Oil and gas extraction) and 334 (Computer and electronic product manufacturing). The latter's import fraction increased from 33% to 54% in 2014, and then declined to 44% in 2019.

C.3 Cost vectors for opex and capex

The link between the energy technologies and IO industries are the cost vectors K in Eqs. (9) and (11). K_j^{capex} is a vector of industries that embeds knowledge of the capital expenditure process of electricity generation technology j, with elements K_{ji}^{capex}: the fraction of capex cost for technology j that is spent on industry i, and $\sum_i K_{ji}^{\text{capex}} = 1$. For example, wind turbines consist of metal products (e.g., for the tower), machinery (e.g., for the nacelle), and electrical equipment (e.g., for the grid connection). Finally, construction work is required to prepare the turbine foundations and installation. Thus, the wind energy capex cost vector $K_{\text{wind}}^{\text{capex}}$ will have non-zero entries for metal industries ($K_{\text{wind,fabricated metal products}}^{\text{capex}} > 0$), certain manufacturing industries, and construction, and all must sum to unity with $\sum_i K_{\text{wind},i}^{\text{capex}} = 1$. Similarly, we require cost vectors of operational (e.g., fuel and maintenance) expenses $K_{\text{j}}^{\text{opex}}$ for disaggregation of the utility sector.

We construct cost vectors for the eight electricity generation technologies by taking the average of previous estimates available in the literature, most of which are based on technical reports by engineering firms or (inter)national agencies, such as IRENA and NREL. Specifically, for wind, solar, geothermal, and biomass both opex and capex we use the mean of values taken from Dell'Anna (2021) and Pollin et al. (2014). NACE industry codes from Dell'Anna (2021) were transformed to NAICS using a crosswalk from Eurostat (Remond-Tiedrez and Defense-Palojarv, 2014). We also use the three different solar and wind vectors and one geothermal cost vector from Garrett-Peltier (2017), which represent 'total cost' according to the authors. However, because the cost items can solely be attributed to materials and construction, we reinterpret these as capex. We further include the cost vectors for coal and natural gas electricity generation by Garrett-Peltier (2017) and Pollin et al. (2014) respectively as opex cost estimates.[27] For gas capex costs, we use the estimates for new oil and natural gas capacity from Pollin et al. (2014). We did not construct any capex cost vectors for coal electricity technologies, as our scenarios assume no new coal electricity generation capacity will be added in the US, nor has any been added since 2014 (EIA, 2021). Similarly, we assume nuclear capacity remains stable and thus leave it out of the analysis. This also implicitly assumes that nuclear capex unit costs will not decline, which is in line with technological trend assessments provided in the literature (e.g., Way et al., 2022).

In addition to electricity generation technologies, we construct capex cost vectors for battery storage from two reports (Feldman et al., 2021; Black & Veatch, 2012). We manually assign the cost items to industries in our IO table, taking the simple mean of the two technical reports. Finally, we take transmission and distribution grid capex vectors from Schreiner and Madlener (2021).[28,29]

Table S3 shows the capex cost vectors used for this study. Note that while we take the cost breakdown per USD spent from the (gray) literature and assume it remains constant over time, we allow the total cost in 2018-USD per MW(h) to vary according to data from NREL's ATB.[30] See Section C.6 for some empirical evidence on the stability of the solar and wind cost breakdown.

In Section D.6, we test the sensitivity of our literature estimates by adding noise

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[27] We note that Garrett-Peltier (2017)'s coal and natural gas cost vectors are sparse and only represent fuel costs, which is the main supply chain cost component for fossil fuel electricity but not the only one. Our matrix inclusion method can account for opex costs beyond fuel costs.

[28] We assume US transmission lines are mostly DC overhead lines (their Table D.2).

[29] Schreiner and Madlener (2021) uses commodity group categories (CPAs), which we translate to IO industries as follows: we match *Services of architecture, engineering and technical and physical investigation* on *Miscellaneous professional, scientific, and technical services*; *Metal products* on *Fabricated Metal Product Manufacturing*; *Ceramics, processed stones and soils* on *Nonmetallic Mineral Product Manufacturing*; both *Electrical gears* and *Electric current, services in electricity, heating and cooling* on *Electrical Equipment, Appliance, and Component Manufacturing*; and finally both *Civil engineering works (Tiefbauarbeiten)* and *Preparation of construction sites, construction installation and other finishing work* on *Construction*.

[30] Except for T&D cost which we calculate separately, as discussed in Section A.1.

to all values of K.

Industries	**Codes**	Wind	Solar	Nat. gas	Coal	Biomass	Geo thermal	Hydro	Battery storage	T&D
Farms	**111CA**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Forestry, fishing, and related activities	**113FF**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Oil and gas extraction	**211**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Mining, except oil and gas	**212**	0.	0.	0.	0.	0.	0.03	0.	0.	0.
Support activities for mining	**213**	0.	0.	0.	0.	0.	0.23	0.	0.	0.
Utilities	**22**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Construction	**23**	0.25	0.2	0.07	0.	0.35	0.15	0.39	0.09	0.09
Petroleum and coal products	**324**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Chemical products	**325**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Plastic and rubber products	**326**	0.05	0.	0.	0.	0.	0.	0.	0.	0.
Nonmetallic mineral products	**327**	0.04	0.03	0.	0.	0.	0.	0.	0.	0.05
Fabricated metal products	**332**	0.18	0.23	0.	0.	0.11	0.1	0.1	0.	0.58
Machinery	**333**	0.22	0.13	0.79	0.	0.47	0.38	0.15	0.	0.
Computer and electronic products	**334**	0.01	0.13	0.14	0.	0.03	0.01	0.01	0.	0.
Electrical equipment, appliances, and components	**335**	0.17	0.15	0.	0.	0.03	0.04	0.08	0.82	0.22
Wholesale trade	**42**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Rail transportation	**482**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Truck transportation	**484**	0.01	0.	0.	0.	0.	0.	0.	0.	0.
Pipeline transportation	**486**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Real estate	**ORE**	0.01	0.	0.	0.	0.02	0.02	0.04	0.	0.
Federal Reserve banks, credit intermediation, and related activities	**521CI**	0.	0.	0.	0.	0.	0.01	0.01	0.	0.
Insurance carriers and related activities	**524**	0.01	0.	0.	0.	0.	0.	0.	0.	0.
Miscellaneous professional, scientific, and technical services	**5412OP**	0.04	0.1	0.	0.	0.	0.02	0.22	0.05	0.06
Management of companies and enterprises	**55**	0.01	0.02	0.	0.	0.	0.02	0.	0.04	0.
Accommodation	**721**	0.0005	0.	0.	0.	0.	0.	0.	0.	0.
Food services and drinking places	**722**	0.0005	0.	0.	0.	0.	0.	0.	0.	0.
Administrative and support services	**561**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Other transportation and support activities	**487OS**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Legal services	**5411**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Sum		1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0

Table S3: **Capex cost vectors of electricity generation technologies.** The estimates we use are the mean of values taken from the literature with some manual adjustments for the 71-industry US input-output table. Coal and Nuclear capex is zero as we assume no new coal electricity generation capacity will be built and nuclear capacity will remain constant. T&D is Transmission and Distribution.

C.4 US electricity sector disaggregation

We apply the opex cost vectors to the procedure of Section B.6 to disaggregate the IO tables.

In practice, we perform the procedure twice. We will first discuss how we disaggregate the Utility sector into three more detailed utility sectors, one of which concerns electricity generation and distribution. Following this, we will discuss how we further disaggregate the electricity sector into detailed generation and transmission sectors.

Utilities split in electricity, natural gas direct distribution, and water and sewage systems We disaggregate the Utility sector (NAICS code 22) into its three more detailed components: Electric power generation, transmission and distribution (NAICS code 2211), Natural gas distribution (2212), and Water, sewage, and other systems (2213). The 2018 IO table only contains the aggregate Utility sector, but the (latest) 2012 detailed IO table contains the three more detailed sectors. For the three more detailed utility sectors, we do have 2018 data on their total output (Bureau of Economic Analysis, 2022a). We first isolate both the production and output recipes of the 2012 utility sectors. We crosswalk all non-utility sectors to match the 70 other industries available in 2018, and thus end up with three output- and production recipes associated with 73 sectors.

We perform the disaggregation procedure of Section B.6.1 to update the 2012 production and output recipes to fit the 2018 table. This created a new 2018 IO table with 73 industries.[31]

Electricity sector split in eleven sub-industries The new IO table with 73 industries contains one electricity generation and distribution sector, which we further split in eleven sectors consisting of eight specific electricity generation technologies, one 'other' electricity generation technology, and two sectors for electricity transmission and distribution respectively:

1. Hydroelectric Power Generation (NAICS 221111) (short name: Hydro)
2. Gas Electric Power Generation (221112[32]) (Gas)
3. Coal Fuel Electric Power Generation (221112[32]) (Coal)
4. Nuclear Electric Power Generation (221113) (Nuclear)
5. Solar Electric Power Generation (221114) (Solar)
6. Wind Electric Power Generation (221115) (Wind)

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[31] Because we update the 2012 IO table with 2018 data, this method is equivalent to the biproportional fitting method for projecting tables into the future mentioned before in Blair and Miller (2009).

7. Geothermal Electric Power Generation (221116) (Geothermal)
8. Biomass Electric Power Generation (221117) (Biomass)
9. Other Electric Power Generation (221118) (Other)
10. Electricity transmission and control (221121) (Trans)
11. Electric power distribution (221122) (Dist)

In this disaggregation, we follow BEA's industry classification at the sixth digit level, with the added benefit that for all these sectors we have 2018 total output data from BEA (see Table S4).[32] In the main text, we combine the final two industries (Trans and Dist) together into one Transmission and Distribution (T&D) sector.

Electricity generation	2018 output in million (2018-USD)
Hydroelectric power generation	3,045
Fossil fuel electric power generation	100,489
Nuclear electric power generation	35,737
Solar electric power generation	779
Wind electric power generation	6,458
Geothermal electric power generation	1,376
Biomass electric power generation	1,066
Other electric power generation	230
Electric bulk power transmission and control	12,403
Electric power distribution	240,901

Table S4: **Total output of the electricity sector.** Source: Bureau of Economic Analysis (2022a). In our analysis, we split the fossil fuel electric power generation output in coal (43%) and gas (57%), using the relative numbers in GWh electricity generation output for the US in 2018 from the EIA.

As mentioned in Section B.3, battery storage is not part of the Utility industry, and we model that separately via a final demand inclusion as explained in Section C.3.

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[32] BEA does not distinguish between fossil fuel technologies. Gas and Coal electric power generation are both part of the same Fossil Fuel Electric Power Generation industry (NAICS 221112). We use additional data by the US Energy Information Administration (EIA) on total GWh electricity production to be able to distinguish between Coal and Natural gas powered electricity plants (Bureau of Economic Analysis, 2022a).

We use the literature opex cost vectors discussed in Section C.3 and Table S5 as initial estimates of the production recipes. We did not prepare opex cost vectors for Trans, Dist, Nuclear, and Other. We initialize these instead with the same production recipe as the higher level industry (*Electricity generation and distribution and transmission* (2211)), excluding any obvious fuel costs (mining, extraction, refineries, agriculture, and pipeline transportation). For Nuclear (221113), we make an extra manual modification and assume it requires nuclear fuel from the *Chemical industry* (325), as explained in the final paragraph of this section.

We make three further modifications in order for the disaggregation procedure to work. First, the literature estimates are often not exhaustive and only highlight the most relevant parts of the production recipes. For example, the fossil fuel production recipes do not include spending on the utility industry that provides electricity, water, and gas, which is a cost they would incur. Zero-valued entries remain zero in the disaggregation algorithm. Therefore, it is important to initialize a low but non-zero value for any sectors that are potentially non-zero. We assign 2% spending on *Utilities* (just less than half of the original 4.5% that the original Utilities sector spent on Utilities) to *Fossil fuel electricity generation.* For all other industries that are not mentioned in the literature Table S5, we assume relative spending by all electricity generation sectors equal to the aggregated *Electricity generation and transmission sector* (2211).

Second, zero-valued entries can lead to matrix inversion problems. We set any zero-valued entry to the equivalent of 2018-USD 1,000. Then we use the disaggregation procedure from Section B.6 to fit according to the constraints as detailed above. After fitting, the biomass fuel component falls away completely as agriculture is not an input to the utility sector in the official IO table. We make the decision to manually add agricultural inputs for biomass.

Third, we assume the value-added components are the same across electricity sectors, except for spending on employee compensation, which we assume scales with total wages paid in that sector. We calculate total wage spending by multiplying the number of workers in each electricity sector with their mean wage as reported by BLS (Bureau of Labor Statistics, 2021). We scale the employee compensation part of value added with the total wage that is spent in that sector. The other components (taxes, subsidies, and gross margin) we assume to be constant across the *Electricity generation and transmission sectors* (2211xx). For the Solar electricity generation sector, scaling value added with employee compensation results in a value added that is larger than total output, which should not be possible. We lower it proportionally so that value added represents 98% of total output, and 2% intermediate spending.

See Table S6 for the top 25 industries by input into the electricity sectors.

Nuclear fuel Nuclear fuel is an important input for the Nuclear electricity generation sector. From the US Energy Information Administration (EIA, 2022b), we learn that about 1/5th (11 million ton) of nuclear fuel was produced domestically in 2018, and that the total costs of this was about 480 million 2018-USD, about 1.3% of total nuclear electricity output.

We use the IO data to find the right source of nuclear fuel. Three candidates are: *Uranium mining*, *Uranium refining*, and/or the *Chemical industry*. In the 2018 IO data *Uranium Mines* are grouped together with all other mines under a generic mining sector (NAICS 212), and it is unclear whether any uranium is used this way or if all items relate to coal, a ubiquitous mining good in electricity generation. The more detailed 2012 tables can help here. Uranium mines are classified under NAICS 212291 (grouped with gold and miscellaneous metals as 2122A0), and uranium smelting and refining are grouped with all non-ferrous metal smelting and refining (331410), and/or rolling, drawing, alloying of nonferrous metals (331490). The combined use by the *Electricity generation and transmission sector* of products from all three sectors (2122A0, 331410 and 331490) in 2012 was 1 million 2012-USD ($< 0.001\%$ of total electricity output), not enough to account for nuclear fuel costs.

Industry	Code	wind		PV		Hydro		Geothermal		Biomass		Gas	Coal
Farms	111CA	0	0	0	0	0	0	0	0	0	0.29	0	0
Forestry, fishing, and related activities	113FF	0	0	0	0	0	0	0	0	0	0.29	0	0
Oil and gas extraction	211	0	0	0	0	0	0	0	0	0	0.14	0.5	0
Mining, except oil and gas	212	0	0	0	0	0	0	0	0	0	0	0	0.5
Utilities	22	0	0.25	0	0.25	0	0.8	0	0.1	0	0.08	0	0
Construction	23	0.02	0.25	0	0.25	0	0	0	0.5	0	0.02	0	0
Petroleum and coal products	324	0	0	0	0	0	0	0	0	0	0.07	0.25	0.5
Plastic and rubber products	326	0.05	0	0	0	0	0	0	0	0	0	0	0
Machinery	333	0.3	0.25	0.15	0	0.35	0.1	0.35	0	0.15	0	0	0
Computer and electronic products	334	0.075	0	0.075	0.125	0.075	0	0.075	0	0.025	0	0	0
Electrical equipment, appliances, and components	335	0.075	0	0.075	0.125	0.075	0	0.075	0	0.025	0	0	0
Wholesale trade	42	0	0	0	0	0	0	0	0	0.3	0	0	0
Rail transportation	482	0.005	0	0	0	0	0	0	0	0.2	0.02	0	0
Truck transportation	484	0.005	0	0	0	0	0	0	0	0.2	0.05	0	0
Pipeline transportation	486	0	0	0	0	0	0	0	0	0	0	0.25	0
Real estate	ORE	0.3	0	0.2	0	0.3	0	0.3	0	0	0	0	0
Federal Reserve banks, credit intermediation, and related activities	521CI	0.17	0	0.5	0	0.2	0	0.2	0	0.1	0	0	0
Miscellaneous professional, scientific, and technical services	5412OP	0	0.25	0	0.25	0	0.1	0	0.4	0	0.04	0	0
Source		Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Garret-Peltier 2017 Pollin	Garret-Peltier 2017 Pollin

Table S5: **Operational expenses (opex) cost vectors from the literature.**

Enriched nuclear fuel can also be an output of *Other Basic Inorganic Chemicals Manufacturing* (NAICS 325180). In 2012, the use by *Electricity generation and transmission sector* (221100) of products from NAICS 325180 was about 166 million 2012-USD (182 million 2018-USD), domestic and imported. In 2018, the *Utility* sector (220000) in total used products from the more aggregate *Chemical manufacturing* (NAICS 325) as a whole for about 2 billion 2018-USD in 2018, enough to cover the uranium input. We thus decided to assign the full 1.3% of Nuclear fuel cost to sector 325.

C.5 Electricity generation outside the BEA utilities sector not in scope

We only model electricity generation that happens in NAICS industry 221100, plus commercial and rooftop solar, battery storage, and T&D in NAICS industries 22121 and 22122. This leaves out electricity production that may happen in other sectors, such as government enterprises and waste incinerators.

Government enterprises that might also produce electricity are out of scope (specifically industry codes S00101 and S00202 in the detailed classification for federal and state/local electric utilities respectively, which are aggregated in GFE and GSLE in the 2018 BEA respectively). These might comprise about 15% of total electricity sector output (Bureau of Economic Analysis, 2022a). We took this decision as the available data is often mixed with other data on government branches. Government utilities are not a separate industry in the latest BEA IO tables, nor an employment industry in the BLS data. Manually disaggregating the government industries for IO and occupational inclusion would add more noise to our analysis.

We also do not consider electricity generated by the *Solid Waste Combustors and Incinerators* industry (NAICS 562213, which is part of the *Waste management and remediation services* [NAICS code 562] in the IO table).

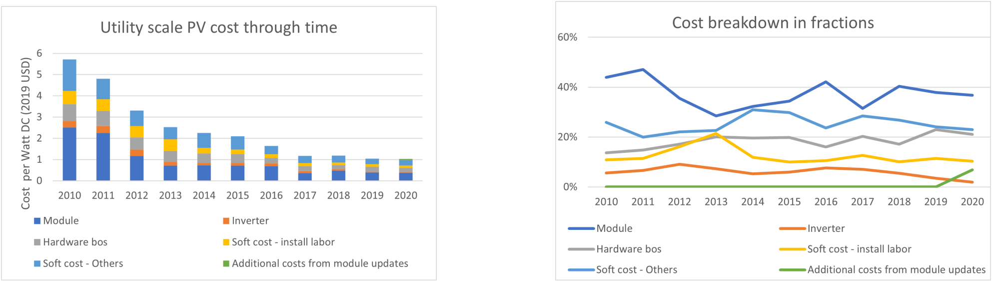
	Total	Hydro	Nuclear	Solar	Wind	Geo thermal	Biomass	Trans	Dist	Other	Gas	Coal
221100	**3.9%**	6.0%	4.3%	0.2%	3.4%	1.4%	0.6%	3.3%	5.4%	5.4%	0.1%	0.1%
imports	**3.7%**	2.1%	3.8%	0.2%	3.8%	3.9%	2.0%	2.9%	4.8%	4.8%	0.9%	0.8%
561	**3.1%**	1.8%	3.3%	0.1%	3.3%	3.3%	1.7%	2.5%	4.1%	4.1%	0.8%	0.7%
211	**2.9%**	0.0%	0.0%	0.0%	0.0%	0.0%	7.6%	0.0%	0.0%	0.0%	0.0%	20.1%
324	**2.6%**	0.0%	0.0%	0.0%	0.0%	0.0%	2.5%	0.0%	0.0%	0.0%	15.4%	6.6%
GSLE	**2.2%**	1.3%	2.3%	0.1%	2.3%	2.3%	1.2%	1.7%	2.9%	2.9%	0.5%	0.5%
212	**2.1%**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	19.2%	0.0%
23	**1.7%**	0.0%	1.9%	0.2%	4.2%	7.8%	0.2%	1.4%	2.4%	2.4%	0.0%	0.0%
5412OP	**1.6%**	0.9%	1.8%	0.2%	3.8%	6.2%	0.3%	1.3%	2.2%	2.2%	0.0%	0.0%
487OS	**1.6%**	0.9%	1.7%	0.1%	1.7%	1.7%	0.9%	1.3%	2.1%	2.1%	0.4%	0.3%
42	**1.4%**	0.0%	1.6%	0.0%	0.0%	0.0%	2.5%	1.2%	2.0%	2.0%	0.0%	0.0%
521CI	**1.2%**	1.7%	1.3%	0.3%	2.6%	3.1%	0.8%	1.0%	1.6%	1.6%	0.0%	0.0%
486	**1.2%**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.4%
482	**1.0%**	0.0%	1.1%	0.0%	0.1%	0.0%	1.9%	0.8%	1.4%	1.4%	0.0%	0.0%
484	**0.9%**	0.0%	1.0%	0.0%	0.1%	0.0%	2.1%	0.8%	1.3%	1.3%	0.0%	0.0%
5411	**0.7%**	0.4%	0.8%	0.0%	0.8%	0.8%	0.4%	0.6%	1.0%	1.0%	0.2%	0.2%
ORE	**0.6%**	2.3%	0.6%	0.1%	4.1%	4.2%	0.0%	0.5%	0.8%	0.8%	0.0%	0.0%
221300	**0.6%**	0.9%	0.6%	0.0%	0.5%	0.2%	0.1%	0.5%	0.8%	0.8%	0.0%	0.0%
4A0	**0.5%**	0.3%	0.5%	0.0%	0.5%	0.5%	0.3%	0.4%	0.6%	0.6%	0.1%	0.1%
514	**0.4%**	0.3%	0.5%	0.0%	0.5%	0.5%	0.2%	0.4%	0.6%	0.6%	0.1%	0.1%
513	**0.4%**	0.2%	0.4%	0.0%	0.4%	0.5%	0.2%	0.3%	0.6%	0.6%	0.1%	0.1%
325	**0.4%**	0.2%	1.1%	0.0%	0.4%	0.4%	0.2%	0.3%	0.5%	0.5%	0.1%	0.1%
722	**0.4%**	0.2%	0.4%	0.0%	0.4%	0.4%	0.2%	0.3%	0.5%	0.5%	0.1%	0.1%
5415	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
721	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
532RL	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
333	**0.2%**	1.8%	0.1%	0.0%	4.0%	2.5%	0.6%	0.1%	0.1%	0.1%	0.0%	0.0%

Table S6: **Final production recipes imputed.** This table only shows the top 26 industries on which the aggregated *Electricity generation and transmission* sector spends more than 0.2% of total output (left-most column). Including all industries and value added, the columns sum up to 100% of output.

C.6 Cost breakdown through time

Throughout our analysis, we assume that the spending breakdown per energy technology is constant. We assume cost-factor neutral technical change, meaning that we allow for unit cost per technology to change, but not how each dollar is spent (c.f. Hicks-neutral technical change). We think this assumption is reasonable based on two empirical sources for solar and wind cost breakdown over time: NREL's ATB solar cost data, and Elia et al. (2020)'s analysis of wind power data.

From NREL's ATB data over time, we find that while the cost for utility-scale solar PV installations declined almost five-fold in the years 2010–2020, the breakdown of these costs into several cost buckets has remained remarkably stable (Fig. S5). While there are fluctuations, no clear pattern can be discerned over the entire period. We use this as evidence to assume that although costs are likely to decline in the future according to technology learning curves, the relative breakdown of cost elements will remain constant over time.



(a) Cost per Watt DC

(b) Cost fraction of total

Figure S5: **Utility-scale PV cost through time.** a) The breakdown per year in constant 2019-USD per Watt DC output. b) The fraction of each of the cost components through time. Data from NREL (Feldman et al., 2021).

Further evidence for the case of wind turbines comes from Fig. 8 of Elia et al. (2020), which looks at the US wind turbine price per kW breakdown for the period 2005-2017. Labor costs are responsible for a 15% to 23% share of the turbine price, with the former estimates most prevalent for the 2005-2008 period. While there are clear fluctuations in different price components, there is no clear trend visible in labor cost as percentage of the wind turbine price, especially after 2009.

C.7 BEA to BLS industry and occupations crosswalk

The Bureau of Labor Statistics (BLS) publishes employment data for industries and occupations at various levels of detail. We use the level of industry detail that matches with that of the BEA industries.[33] A correspondence table from the EPA is used to connect the two classifications, which gives mostly one-to-one or one-BEA-to-many-BLS matches (Environmental Protection Agency, 2022). This allows us to directly link the number of workers per occupation to the BEA industries, or the sum of several BLS industries linked to one BEA industry.[34] Extra care was given to distinguish between government-run and private education services, which are part

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[33] Except for the disaggregated Utility sector: see paragraph below.

[34] e.g. BEA industry 315AL (Apparel and leather and allied manufacturing) consists of BLS industries 351500 (Apparel manufacturing) and 351600 (Leather and allied product manufacturing).

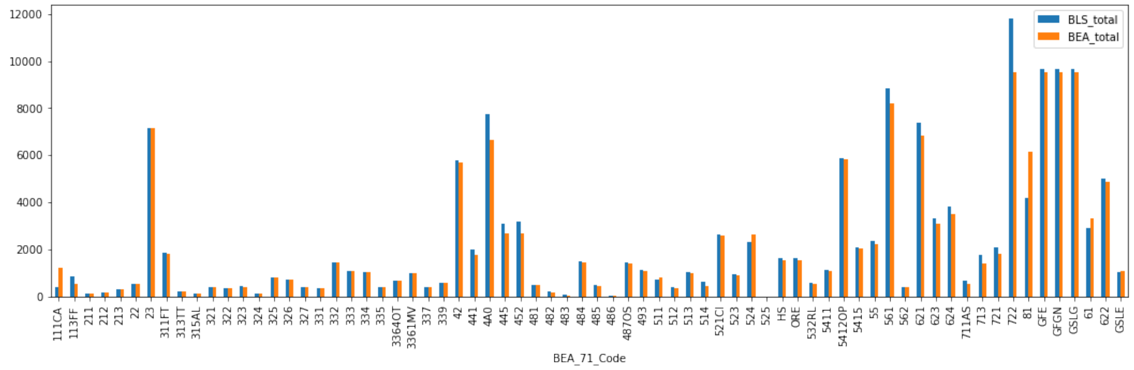
of government services in the BEA data, and education services for BLS. The same is true for government-run and private hospitals. We exploit the BLS information on ownership to get the distinction right.

Two sets of industries had many-to-one relationships. While BLS distinguishes governments by regional level (local, state, federal), BEA distinguishes between level (federal and state/local) and function (general government and government enterprises). We sum all BLS government codes and assign them to the BEA government codes (except local/state government enterprises and *GFGD*, the defense part of the federal general government), with fractions based on BEA spending on employee compensation. We thus assume the relative occupational make-up of government services is the same on the state and federal level. 28% of government employees work on the federal level. The aforementioned government-run hospital and education services were matched on the remaining local/state government enterprise sector.

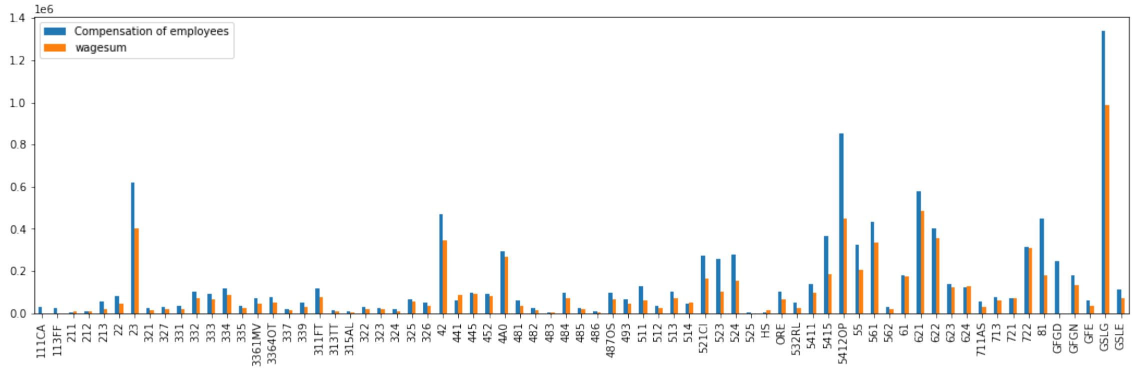
The second many-to-one relation concerns the real estate sector. BEA distinguishes between Housing (HS) and Other real estate (ORE) sectors, which both map on BLS's more general 531000 (Real Estate) sector. We assume HS and ORE sectors have the same occupational make-up as the BLS's 531000 sector, with the absolute number split according to the relative difference in employee benefits spending by HS and ORE respectively. This results in our estimate that 17% of Real Estate workers work in the HS sector, and 83% in the ORE sector.

Agricultural and government defense industries are not included in the BLS data. We leave defense (GFGD) out of the full analysis and both out of the occupational analysis.

In Fig. S6, we compare the two datasets as a sanity check of our harmonization. BEA also publishes numbers of total full-time equivalent workers per industry. We find a good agreement with BLS's total employment in Fig. S6a, with the largest difference for Other services (81), which has more workers according to BEA than to BLS. This might be due to the eclectic nature of this industry or measurement differences on either side.



(a)



(b)

Figure S6: **Comparison of BLS and BEA industry data.** a) Thousands of workers in the BLS dataset vs the thousands of full time equivalent workers in BEA; b) the compensation of employees according to 2018 IO tables published by BEA, and the sum of wages of all employees working in the industries in 2018 according to data from BLS, both in millions of 2018-USD. Note that we do not have wage data for military (GFGD) or agricultural (111CA and 113FF) workers.

We also compare total employee compensation as published by BEA with total wage spending according to BLS. Employee compensation includes everything the employer pays for its workers, including additional taxes and bonuses that are not reflected in average wages. It is almost always higher than the wage a worker receives but can also be lower due to subsidies. The difference is often larger for high-paid workers. We conclude that Fig. S6b reflects this to a large extent and that our harmonization can be used.

Electricity sector industries and workers. As explained in Section C.4, we split the utilities sector into 13 industries, including eight electricity generation technologies. Since 2015 BLS reports on the number of workers and their occupation per electricity generation technology, we incorporate their data for 2018 in our analysis. Following on from Table S1, we show which BLS and BEA industries match on the IO classifications for industries in Table S7.

Four things should be noted. First, *Battery storage* is not present as a separate electricity technology in either BEA or BLS. As explained further in Section B.3, we add battery storage opex workers manually, with a similar occupational makeup as its capex workers. Second, as mentioned before, neither BEA nor BLS split fossil fuel electricity generation into gas or coal. We use EIA electricity production data for that split,[35] both for the BEA and BLS data. Third, we combine transmission and distribution (T&D) in our IO analysis, which are separated in the BEA data. We simply sum them together. BLS does not report any data on electricity transmission and distribution but does report figures on the NAICS 2211 level (*Electric power generation, transmission and distribution*). We assume any workers in NAICS 2211 that are not accounted for by the other sub-industries work in T&D. Last, while we do not report on *Other electric power generation*, it is included in our IO table. As we assume all electricity generation comes from the technologies identified in Table S1, the 'Other' sector output was set to always be zero.

The Utilities sector employed over half a million workers in 2018, almost 400,000 of which were working in electricity generation, transmission and distribution. Just over 150,000 workers were directly involved with electricity generation facilities, the majority in fossil fuel (89,000), followed by nuclear (44,000). Total employment in renewables (hydro, wind, solar, biomass, and geothermal) stood at about 17,000 in 2018, with about a third of that for wind and another third for hydro.

Because the electricity generation sectors are small compared to the more aggre-

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[35] `https://www.eia.gov/energyexplained/us-energy-facts/`

IO industry	NAICS code	BLS industry	BEA industry
Battery	-	-	-
Bio	221117	Biomass electric power generation	Biomass Electric Power Generation
Coal Gas	221112	Fossil fuel electric power generation	Fossil Fuel Electric Power Generation
Geo	221116	Geothermal Electric Power Generation	Geothermal electric power generation
Hydro	221111	Hydroelectric Power Generation	Hydroelectric power generation
Nuclear	221113	Nuclear Electric Power Generation	Nuclear electric power generation
Solar	221114	Solar Electric Power Generation	Solar electric power generation
Wind	221115	Wind Electric Power Generation	Wind electric power generation
Other	221118	Other Electric Power Generation	Other electric power generation
T&D	221121	-	Electric bulk power transm. and control
	221122	-	Electric power distribution
Gas dist	221200	Natural Gas Distribution	Natural gas distribution
Water and sewage	221300	Water, Sewage and Other Systems	Water, sewage and other systems

Table S7: **IO, BLS, and BEA industry matching for the disaggregated Utility sector.**

gated sectors, the occupational data is not as detailed and more error prone than the utilities sector data as a whole. This is also highlighted by the larger relative standard error reported by BLS. BLS gives both the total number of workers per industry and an occupational breakdown for most workers. We first matched the occupational breakdown to our occupational list. Some of these have censored values. In the OEWS files, these occupations have two stars (**) instead of an estimated number of workers for that occupation-industry pair. We infer from more aggregated occupation levels how many workers there should roughly be. We impute those values with those in Table S8. Additionally, the utility industries report total employment figures that are larger than the sum of their detailed occupation list. We take two approaches. First, for the high-level utility industries (first 221000 (Utilities), then 221100 (Electric Power Generation, Transmission and Distribution), 221200 (Natural Gas Distribution), and 221300 (Water, Sewage and Other Systems)), we assign missing workers to their existing occupations proportional to employment.

Secondly, the proportion of missing workers is larger for smaller sectors. For example, 900 of 2,560 Solar electricity generation workers did not have detailed occupations assigned in the BLS data. This means that those industries often also report on a smaller number of occupations. Potentially, there are unreported occupations. We call these *missing* occupations. We know how many there are as BLS also reports the total number of workers per industry regardless of their occupation. We assign these workers to occupations as follows:

1. We sum all workers to the *minor* occupation level (often 3-digit level). If that value is larger than OEWS reports at that minor level, we add workers to all occupations in that minor level, including those that are not in the OEWS data.

2. We next sum all workers to the *major* occupation level (often 2 digits). These occupation categories group together dozens of more detailed occupations. If they sum to a total number of workers that is lower than OEWS reports, we add workers only to those occupations that BLS reports on or to those occupations we had added in the previous step.

3. We remove any *tiny* occupations (i.e., those industry-occupations pairs with less than 30 workers or 0.2% of industry total, and add those workers proportionally to all other occupations in that industry.

OEWS does not report an occupational breakdown for Electric power Transmission and Distribution industry (NAICS code 221120). We assume that all workers in 221100 (Electric Power Generation, Transmission and Distribution) that do not work in Electricity generation (NAICS 22111) work for Electric Power Transmission and Distribution.

Finally, we split fossil fuel electricity generation in two, one dedicated to coal and the other to natural gas based electricity generation. The occupational profiles are kept identical, but the total number of workers is split according to the electricity output as reported by EIA (2022a).

In Section D.6, we perform a sensitivity analysis on the number of workers per occupation per industry using the standard errors reported by BLS. That analysis shows that the impact on the results is larger for small but fast-growing occupations such as Wind Turbine Service Technicians.

BLS NAICS code	BLS OCC code	Total employment imputation
221000	17-1010	50
221000	17-1020	980
221000	21-1090	0
221000	41-9040	120
221000	47-4070	250
221000	47-5020	210
221000	53-6030	80
221000	53-6090	80
221100	17-3010	2340
221100	19-4040	80
221100	21-1090	0
221100	41-3030	160
221100	49-2020	440
221100	49-9052	1660
221100	51-8090	1100
221100	53-2010	0
221100	53-6090	90
221200	17-1020	460
221200	41-9040	120
221200	41-9099	60
221200	43-4190	100
221200	43-5070	30
221200	43-9050	70
221200	49-9051	2650
221200	51-8010	830
221200	51-8020	710
221200	53-6030	80
221300	17-3010	80
221300	33-9030	0
221300	47-3010	170
221300	47-4070	270
221300	49-9051	120
221300	51-8010	165
221300	51-8090	165
221300	51-9199	160
221300	53-7030	40
221111	13-1070	75
221111	13-1080	75
221111	51-8090	70
221111	51-9060	110
221111	51-9198	100
221112	53-2010	0
221115	49-9041	430
221115	15-1120	50
221115	51-1010	80
221118	51-8010	390

Table S8: **All employment imputations in the industry-occupation matrix B_{2018}.**

C.8 Occupation crosswalk Census - BLS

The crosswalk includes occupations that are grouped together. We perform a manual operation to split them. For example, we split 25-90XX (Other Education, Training, and Library Occupations) into four occupations that BLS reports on within that group: 25-9010 Audio-Visual and Multimedia Collections Specialists; 25-9020 Farm and Home Management Advisors; 25-9030 Instructional Coordinators; 25-9090 Miscellaneous Education, Training, and Library Workers). Table S9 shows the full list of imputed alterations that we performed.

2010 SOC Code	Imputed
15-113X	15-1132
15-113X	15-1133
25-90XX	25-9010
25-90XX	25-9020
25-90XX	25-9030
25-90XX	25-9090
31-909X	31-9093
31-909X	31-9099
33-909X	33-9092
33-909X	33-9099
37-201X	37-2011
37-201X	37-2019
39-40XX	39-4000
47-50XX	47-5050
47-50XX	47-5090
49-209X	49-2094
49-209X	49-2095
49-904X	49-9041
49-904X	49-9045
49-909X	49-9093
49-909X	49-9099
53-40XX	53-4040
53-40XX	53-4090
53-60XX	53-6040
53-60XX	53-6090

Table S9: **SOC crosswalk imputation of missing values.**

We drop two census occupations that are not in BLS: 6100 (*Fishers and related fishing workers*; soc code 45-3011) and 6110 (*Hunters and trappers*; soc code 45-3021).

The final list of BLS occupations has 539 entries on the BLS side and 529 census occupations. Our set of BLS occupations comprises 138 6-digit occupations, 497 5-digit occupations, and 3 4-digit occupations.

C.9 Occupational typology

We list all 'Consistent growth' occupations in Table S10, all 'Consistent decline' occupations in Table S11, and all 'Temporary growth' occupations in Table S12.

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
47-2230	Solar Photovoltaic Installers	46,010
49-9051	Electrical Power-Line Installers and Repairers	70,240
49-9080	Wind Turbine Service Technicians	58,000

Table S10: **Consistent growth occupations.** All occupations that are affected more than 1% of total pre-transition employment and see a demand increase in both the scale-up and scale-down phase.

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
17-2150	Mining and Geological Engineers, Including Mining Safety Engineers	98,420
47-5040	Mining Machine Operators	53,090
47-5050	Rock Splitters, Quarry	35,760
47-5060	Roof Bolters, Mining	59,090
47-5090	Miscellaneous Extraction Workers	54,300
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	80,040
51-8010	Power Plant Operators, Distributors, and Dispatchers	81,760
51-8090	Miscellaneous Plant and System Operators	66,430
53-7030	Dredge, Excavating, and Loading Machine Operators	48,790
53-7040	Hoist and Winch Operators	56,390
53-7070	Pumping Station Operators	52,510
53-7110	Mine Shuttle Car Operators	56,150
53-7120	Tank Car, Truck, and Ship Loaders	42,330

Table S11: **Consistent decline occupations.** All occupations that are affected more than 1% of total pre-transition employment and see a demand decrease in both the scale-up and scale-down phase.

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
11-3050	Industrial Production Managers	113,370
11-3060	Purchasing Managers	125,630
11-9020	Construction Managers	103,110
11-9040	Architectural and Engineering Managers	148,970
13-1020	Buyers and Purchasing Agents	67,530
13-1050	Cost Estimators	69,710
13-2082	Tax Preparers	46,860
17-2070	Electrical and Electronics Engineers	104,250
17-2110	Industrial Engineers, Including Health and Safety	91,800
17-2130	Materials Engineers	96,930
17-2140	Mechanical Engineers	92,800
17-2170	Petroleum Engineers	156,370
17-2199	Engineers, All Other	99,410
17-3010	Drafters	58,180
17-3020	Engineering Technicians, Except Drafters	61,380
19-4040	Geological and Petroleum Technicians	62,890
41-9030	Sales Engineers	108,610
43-5060	Production, Planning, and Expediting Clerks	50,020
43-5070	Shipping, Receiving, and Traffic Clerks	34,980

Continued on next page

Table S12 – continued from previous page

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
47-1010	First-Line Supervisors of Construction Trades and Extraction Workers	70,540
47-2010	Boilermakers	63,240
47-2020	Brickmasons, Blockmasons, and Stonemasons	52,810
47-2030	Carpenters	51,120
47-2040	Carpet, Floor, and Tile Installers and Finishers	45,330
47-2050	Cement Masons, Concrete Finishers, and Terrazzo Workers	47,340
47-2060	Construction Laborers	40,350
47-2071	Paving, Surfacing, and Tamping Equipment Operators	44,360
47-2072	Pile-Driver Operators	64,360
47-2073	Operating Engineers and Other Construction Equipment Operators	53,030
47-2080	Drywall Installers, Ceiling Tile Installers, and Tapers	50,420
47-2110	Electricians	59,190
47-2120	Glaziers	48,620
47-2130	Insulation Workers	46,910
47-2141	Painters, Construction and Maintenance	43,050
47-2142	Paperhangers	40,840
47-2150	Pipelayers, Plumbers, Pipefitters, and Steamfitters	56,980
47-2160	Plasterers and Stucco Masons	47,610
47-2170	Reinforcing Iron and Rebar Workers	54,670
47-2180	Roofers	43,870
47-2210	Sheet Metal Workers	52,710
47-2220	Structural Iron and Steel Workers	58,170
47-3010	Helpers, Construction Trades	32,900
47-4020	Elevator Installers and Repairers	79,370
47-4030	Fence Erectors	37,650
47-4090	Miscellaneous Construction and Related Workers	43,000
47-5010	Derrick, Rotary Drill, and Service Unit Operators, Oil, Gas, and Mining	52,950
47-5020	Earth Drillers, Except Oil and Gas	47,570
47-5070	Roustabouts, Oil and Gas	40,220
47-5080	Helpers–Extraction Workers	37,660
49-9020	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	50,160
49-9041	Industrial Machinery Mechanics	54,000
49-9043	Maintenance Workers, Machinery	48,720
49-9044	Millwrights	56,250
49-9045	Refractory Materials Repairers, Except Brickmasons	52,510
49-9096	Riggers	51,330
51-1010	First-Line Supervisors of Production and Operating Workers	64,340
51-2020	Electrical, Electronics, and Electromechanical Assemblers	35,910
51-2030	Engine and Other Machine Assemblers	45,330
51-2040	Structural Metal Fabricators and Fitters	41,640
51-2090	Miscellaneous Assemblers and Fabricators	34,300
51-4010	Computer Control Programmers and Operators	43,940
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	36,620
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	40,770
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	40,790
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	36,180
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	41,490
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	36,690
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	41,090
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	44,490
51-4040	Machinists	45,250
51-4050	Metal Furnace Operators, Tenders, Pourers, and Casters	41,160
51-4060	Model Makers and Patternmakers, Metal and Plastic	53,430
51-4070	Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic	34,200
51-4080	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	37,510
51-4110	Tool and Die Makers	53,650
51-4120	Welding, Soldering, and Brazing Workers	43,930

Continued on next page

Table S12 – continued from previous page

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	39,050
51-4192	Layout Workers, Metal and Plastic	47,380
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	34,830
51-4194	Tool Grinders, Filers, and Sharpeners	40,890
51-4199	Metal Workers and Plastic Workers, All Other	38,140
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	35,500
51-9020	Crushing, Grinding, Polishing, Mixing, and Blending Workers	37,960
51-9030	Cutting Workers	35,090
51-9040	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	36,800
51-9050	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	40,610
51-9060	Inspectors, Testers, Sorters, Samplers, and Weighers	42,010
51-9120	Painting Workers	39,850
51-9140	Semiconductor Processors	39,810
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	33,090
51-9194	Etchers and Engravers	34,550
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	35,190
51-9197	Tire Builders	45,530
51-9198	Helpers–Production Workers	29,380
51-9199	Production Workers, All Other	34,490
53-7020	Crane and Tower Operators	58,160
53-7063	Machine Feeders and Offbearers	31,710

Table S12: **Temporary growth occupations.** All occupations that are affected more than 1% of total pre-transition employment and see a demand increase in the scale-up phase and a demand decrease in the scale-down phase.

D Supplemental Results

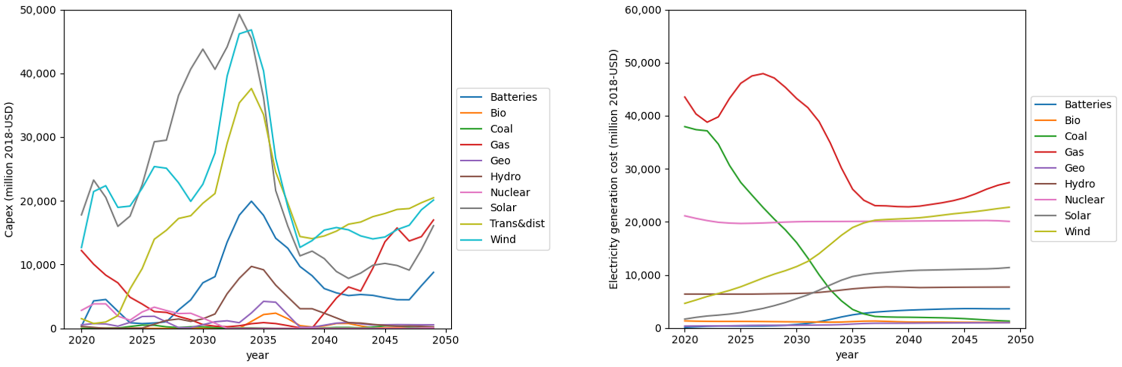
D.1 Capex and opex over time

Fig. S7 shows the results of Eqs. 4 and 5, including the special cases of battery storage and transmission and distribution (T&D) cost, as explained in Sections B.3 and B.2, respectively.

On the capex side, we find a large increase in investment in renewable technologies (solar, wind, batteries) and the transmission and distribution network before 2035 and a decline afterwards in the *95% by 2035* scenario. This is not visible in the *reference* scenario. Beyond 2038, we can see continued higher investments in contrast to the *reference* scenario, especially in T&D.

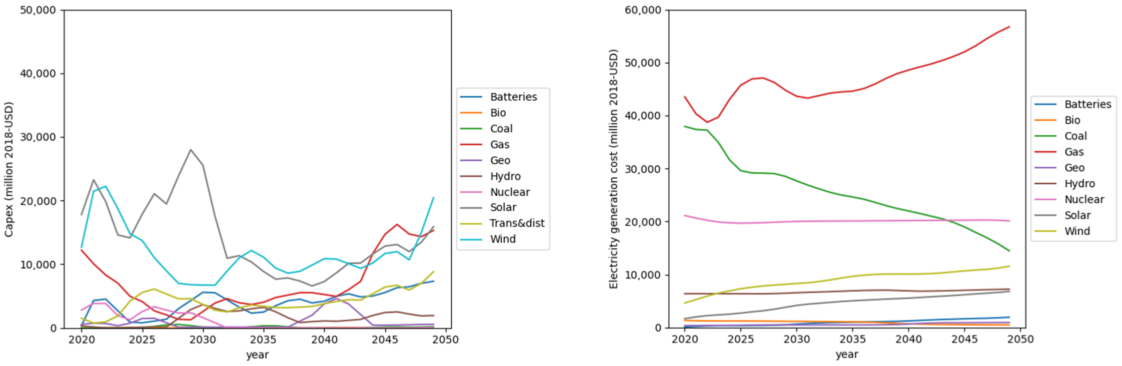
On the opex side, we see that renewable technologies require a larger share of total cost over time in the *95% by 2035* scenario, with most change happening before

2035. In the *reference* scenario, renewable technologies also require more opex, but the largest change to opex is the switch from coal to natural gas.



(a) Capex 95% by 2035

(b) Opex 95% by 2035



(c) Capex reference

(d) Opex reference

Figure S7: **Total capex and opex cost per year for different electricity technologies.** (a) and (b) show the capex and opex per year of the *95% by 2035* scenario, respectively; (c) and (d) show the capex and opex per year of the *reference* scenario.

D.2 95% decarbonisation by 2050

The *95% by 2050* scenario is an alternative NREL scenario that fixes the 95% decarbonization target not at 2035 but at 2050. Below, we reproduce Figs. 1, 2 and 3 for this scenario.

Fig. S8 shows the capacity and generation profiles of this scenario in relationship to the two scenarios of the main text. The *95% by 2050* scenario reaches its decarbonization target 15 years after the *95% by 2035* scenario and has a more gradual transition profile.

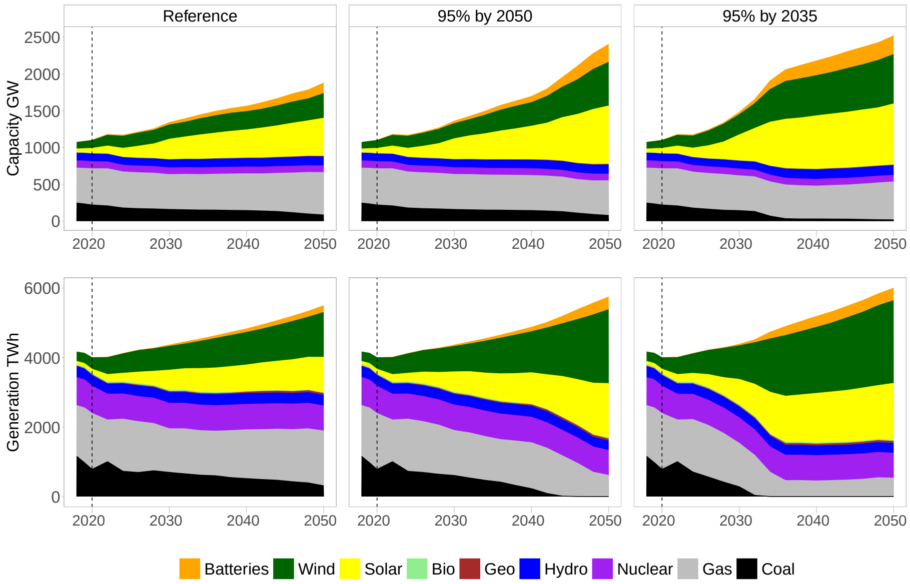
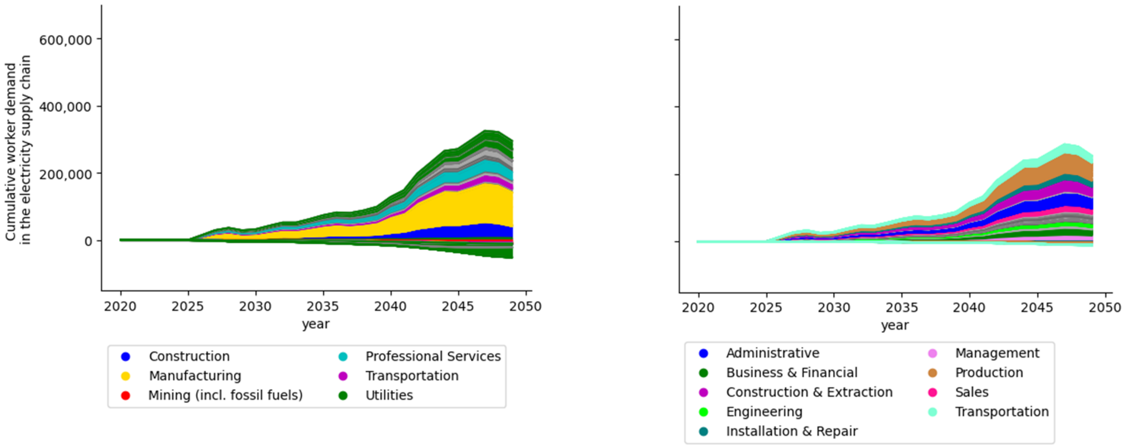


Figure S8: **The NREL reference, *95% by 2050*, and *95% by 2035* scenarios for the US power sector.** The upper panels show the capacities in GW, and the lower panels show the electricity generation in TWh in yearly resolution. On the left, we show NREL's no-new-policy scenario that we use as a reference; in the middle, NREL's fast *95% by 2035* scenario; and on the right, NREL's *95% by 2050* scenario (Cole et al., 2021). Up to 2020, the figures show historical data from the Electric Power Annual 2020 (EIA, 2022a). Technological categories are aggregated according to SM Table S1.



(a) Industries

(b) Occupations

Figure S9: **Overall demand for workers 95% by 2050.** Total additional demand change for workers in the 95% decarbonization by 2050 scenario (a) per aggregated industry and (b) per occupation category. The demand change is net of the NREL *no-new-policy reference* scenario. Industries are plotted at the detailed level used in the analysis (82 industries) but colored by their 2-digit aggregated categories (14 of 20 categories are minimally affected and shown in gray scale). Occupations are plotted at the detailed level used in the analysis (539 occupations) and colored by their 2-digit level aggregation (13 of 22 occupation groups are minimally affected and shown in gray scale). The gray-scaled aggregated industries and occupational groups are labeled in a footnote below Fig. 2 in the main text.

Finally, Fig. S10 reproduces Fig. 3 for the *95% by 2050* scenario, using the same

2021-2033 and 2034-2038 years as in the main text. We now find that many more occupations are minimally affected. The most impacted occupations in Fig. S10 are "Power plant operators" (consistent decline) and "Solar PV installers" and "Wind turbine technicians" (both Consistent growth), which is similar to Fig. 3. However, we do not observe the large group of "Temporary growth" occupations that we saw in Fig. 3.

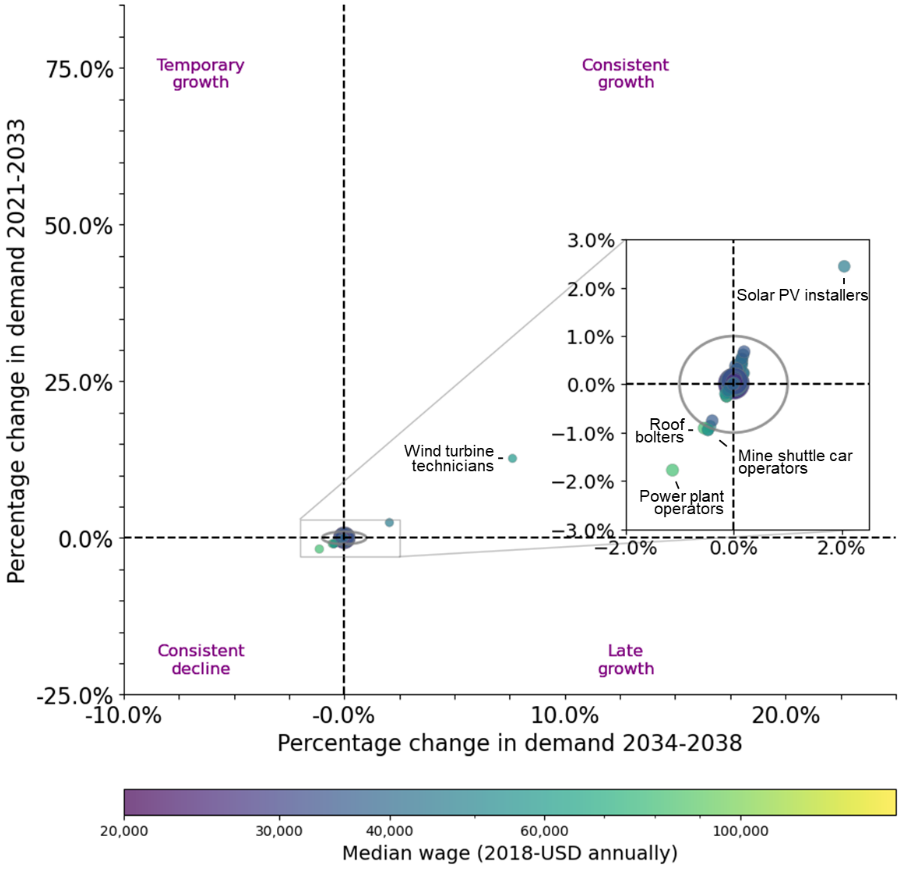
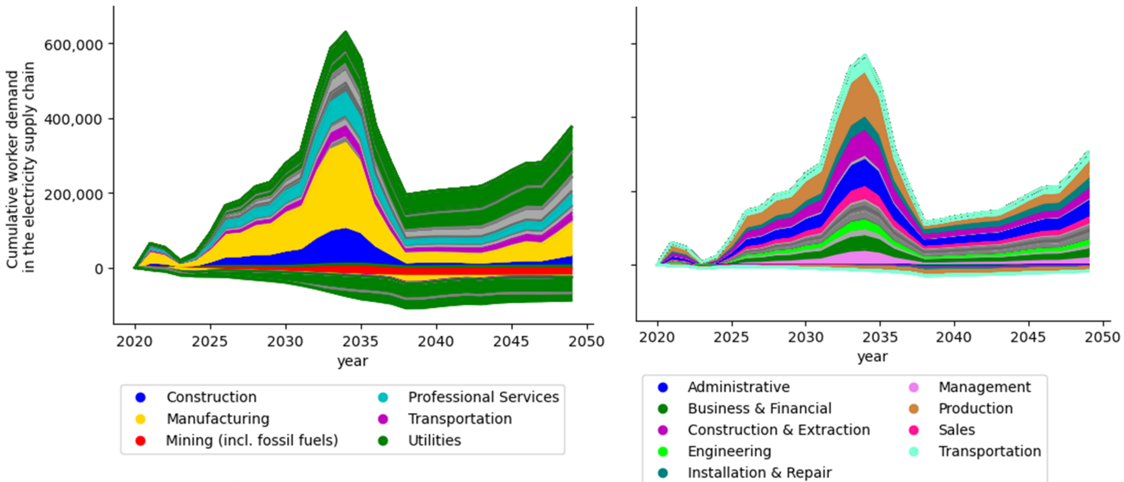


Figure S10: **Occupation demand change relative to employment in the *95% by 2050* scenario**. On the vertical axis, the net demand change between 2021–2034, and on the horizontal axis, the change between 2034–2038. Occupations within the gray circle indicating less than 1% demand change are considered minimally affected; all others are categorized in the labor transition typology that is formed by the four quadrants. Occupations are colored according to their mean wage

D.3 Results not relative to the *reference* scenario

The results presented in the main text are relative to NREL's *no-new-policy reference* scenario. Because of the cost declines in renewables, this *reference* scenario does include some decarbonization driven by cost optimization rather than climate policy. See the left columns of Fig. 1 for the capacity and generation mix in the reference case.

In Fig. S11, we plot the aggregate demand change from 2020 (net per industry (left) and occupation (right) through time for the 95% decarbonization by 2035 scenario. Compared to Fig. 2, we find the same scale-up and scale-down phases, but the steady state phase is less visible. While there appears to be a steady state for the period 2038-2043, employment rises again in subsequent years. This is likely due to the gradual increase in the use of electricity and the end-of-life replacements that are included in the *reference* scenario and transition scenarios alike.



(a) Industries

(b) Industries

Figure S11: **Overall demand for workers (not relative to baseline).** Total additional demand change since 2020 for workers in the 95% decarbonization by 2035 scenario a) per aggregated industry and b) occupation category. Compare to Fig. 2. Industries and occupations are plotted at the detailed level (82 industries and 530 occupations respectively) but colored by their aggregated categories.

Fig. S12 shows some trajectories for selected occupations through time (relative to the *reference* scenario in Fig. S18). We find the main differences in the last decade, 2040–2050. As the *reference* scenario also decarbonizes (but slowly), the difference between the two scenarios becomes smaller in the late 2040s. This causes some occupational trajectories, such as Mining Machine Operators and Solar PV Installers, to trend towards the $x = 0$ line in the 2040s relative to the baseline in

Fig. S18 but not in Fig. S12.

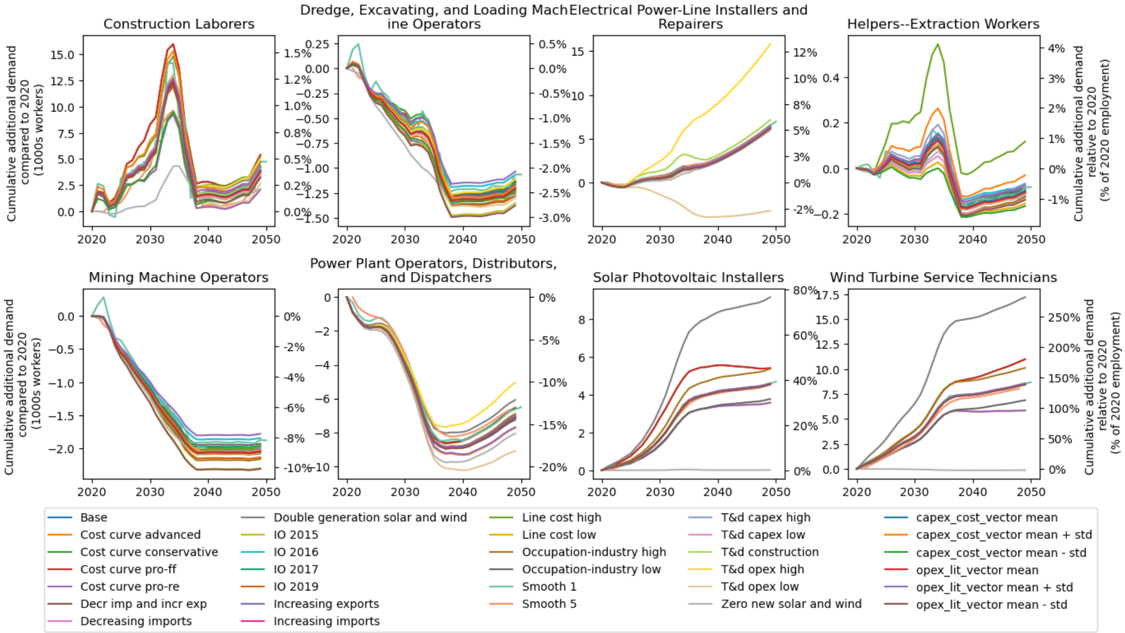


Figure S12: **Demand trajectories for selected occupations (not relative to baseline).**

D.4 Location, skills, and frictions

In this section, we show the current geographical spread and skill content of the occupational typology presented in the main text.

D.4.1 Geographical spread

Our main results are for the US as a whole, but such national aggregation may obfuscate local differences, as mentioned in the main text. In Fig. S13, we show the 2018 average location quotients for different occupational types. Because we do not disaggregate our forward-looking results, we can not confidently predict the places where future jobs will be located. *Consistent growth* occupations were located in 2018 where the US is generating most of its renewable energy: in the south-west, where most utility-scale solar electricity is generated, and the central Great Plains states that see the highest on-shore wind resource and economic potential (McCabe et al., 2022). ‘Temporary growth’ occupations are less concentrated but more prevalent in traditional manufacturing states in the Northeast and Midwest. ‘Consistent decline’ occupations display the highest level of concentration and are mostly located in a few coal and gas-rich states. See SM Section B.8 for more details on how we calculate the location quotients.

While the location quotients of the ‘Consistent decline’ occupations might be a good indicator of where job losses are concentrated, this is not necessarily true for occupations with growing demand. Newer generations of wind turbines, for example, are taller, and wind potential at higher altitudes can be different (McCabe et al., 2022), opening up new places for competitive wind energy generation. And local regulations can change. The best wind turbine locations for the future may thus not be where most wind turbines are located right now. Additionally, the US government’s domestic manufacturing agenda may well benefit places beyond the traditional Rust Belt states (The White House, 2022).

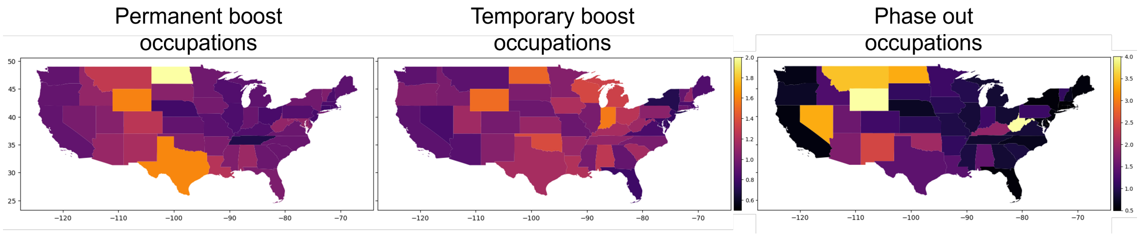


Figure S13: **Average location quotient in 2018 of selected occupations in the three occupation types as defined in the main text.** These may not be the states where future jobs are located. The location quotient of occupation a in state β is $\frac{x_{a,\beta}/x_\beta}{x_a/x}$, with $x_{a,\beta}$ is the number of workers in occupation a in state β, and any subscripts that are left out are summed over (e.g. $x_\beta = \sum_i x_{i,\beta}$). Permanent and Temporary growth occupations share the same colormap; Consistent decline occupations have their own.

D.4.2 Skill content

Skill differences between occupations has been identified in the literature as one of the main factors influencing the ease of transition between occupations (Consoli et al., 2016; Bowen et al., 2018; Saussay et al., 2022). In this section, we highlight the skill content of the occupation typology. We follow Consoli et al. (2016), who quantify the skill categories of Autor et al. (2003) for green jobs. These skill categories are Non-routine analytical (NRA), Non-routine interactive (NRI), Routine cognitive (RC), Routine manual (RM), Non-routine manual (NRM), and the Routine index (RTI index).

In Fig. S14 we find that compared to all other jobs, occupations in the three affected groups in our typology have higher manual and routine (NRM, RTI, RM) skills. The other skills show fewer differences across occupation types on aggregate.

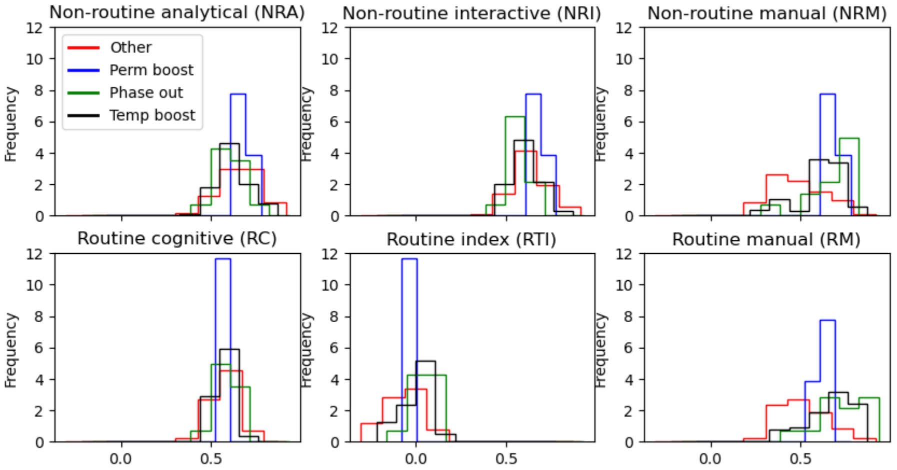


Figure S14: **Average skill content over occupation typology.** Histogram of skill intensity over occupations that see a *Temporary growth* (black), *Consistent growth* (blue), or *Consistent decline* (green). The average skill content of all other occupations is plotted in red.

In Fig. S15, we plot the same skill distribution using the alternative typology definition (see Section B.7). We compute the average skill content of all occupations, weighted by the fraction of workers in an occupation that are part of each type. Fig. S15 shows that for non-routine analytical (NRA), non-routine interactive (NRI), and routine cognitive (RC), the differences between transition workers and all workers distribution are small. However, all affected types of occupations score higher on routine manual (RM) and non-routine manual (NRM) indicators on average.

Figs. S14 and S15 are similar in that all three affected occupation types exhibit higher manual and routine skill levels (NRM, RTI, RM) than the average job.

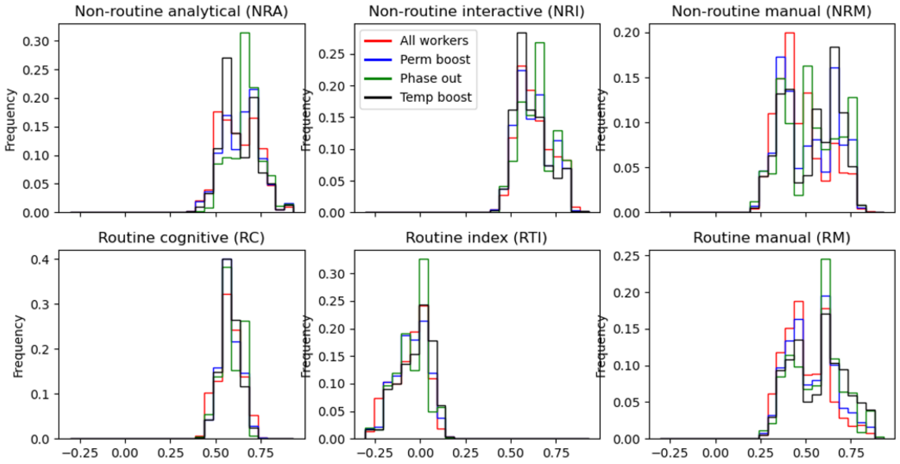


Figure S15: **Average skill content over occupation typology.** Histogram of skill intensity over occupations that see a *Temporary growth* (black), *Consistent growth* (blue), or *Consistent decline* (green), using the alternative typology definition. The average skill content of all workers is plotted in red.

D.4.3 Occupation network frictions and alternative networks

This section expands the assortativity analysis of Table 1 in the main text by incorporating alternative occupational network definitions and the alternative typology. We also discuss the Monte Carlo simulation approach and results that give the confidence intervals for Table 1.

We will first expand the analysis of categorical assortativity and, after that, the analysis of continuous attribute assortativity. We use three networks for our analysis: in addition to the related occupation network, we use an occupational mobility network constructed from census data and a combination of both. For more details on the two networks, see Section A.4.

Categorical assortativity results Table S13 shows the assortativity between the occupational types. All of these results use the categorical assortativity method of Eq. (19). The *Categorical* result on the related network (RN) is the same as in Table 1. The assortativity results of the three individual types are calculated by only including two categories in Eq. (19): that particular type, and an *other* group containing all other occupations.

We find that the categorical results are robust over the networks, if somewhat smaller in magnitude than for the related network. For the individual occupational types, we find that, in particular, the *Temporary Growth* has high assortativity for both networks, in particular for the related occupation network. This indicates that it may be difficult to find a lot of workers to fill vacancies for all the *Temporary growth* jobs simultaneously. Interestingly, the assortativity values for *Consistent growth* and *Consistent decline* occupations are much lower and less significant, indicating that the associated occupations are more spread out in the network. For the occupational mobility network, the *Consistent growth* shock has a slightly negative assortativity, meaning that very few transitions have been observed between them in the past.

	OMN	RN	mixed 50/50
Categorical	0.29***	0.43***	0.39***
Consistent growth	-0.00	0.05**	0.01
Temporary growth	0.28***	0.45***	0.39***
Consistent decline	0.18**	0.13***	0.17***

Table S13: **Network assortativity of the occupational typology of the power sector transition**. OMN = occupational mobility network, RN = related network. ***, **, * indicate results that are greater than 99.9%, 99%, or 95% of values respectively in a Monte Carlo simulation.

In Table S14, we randomize the impact per occupation while keeping the network intact. The standard errors are computed across 100,000 randomizations, which we also use to get confidence intervals for the assortativity results in Table S13. That is, a value in Table S13 gets three (***), two (**), or one (*) star if it is larger in absolute value than 99.9%, 99%, or 95% of randomized runs respectively.

	OMN	RN	mixed 50/50
Categorical	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Consistent growth	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Temporary growth	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)
Consistent decline	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)

Table S14: **Average network assortativity coefficient of occupational typology.** Average of 100,000 randomized runs. OMN = occupational mobility network, CCN = related network. Standard deviation in brackets.

Continuous assortativity The alternative occupational typology is a continuous variable, so we use the weighted continuous assortativity measure of Eq. (17). The results in Table S15 for the scale-up and scale-down phases are the same as in Table 1. These are robust over the different networks, if slightly higher for the scale-up phase in the empirical occupational mobility network, and lower for the scale-down phase.

The results for the 'Consistent growth' and 'Temporary growth' occupations are very similar to the categorical assortativity in Table S13. For 'Consistent decline' occupations the sign is the same, but assortativity in Table S13 is slightly higher and more significant, indicating that the most impacted occupations cluster together more than the impact more broadly.

	OMN	RN	mixed 50/50
2020-2034 (scale-up)	0.08**	0.05***	0.05**
2035-2038 (scale-down)	0.16***	0.26***	0.23***
Consistent growth (alternative)	-0.02**	0.04**	0.02*
Temporary growth (alternative)	0.32***	0.51***	0.46***
Consistent decline (alternative)	0.07*	0.06**	0.06**

Table S15: **Assortativity of the shock relative to employment on different occupation networks.** OMN = occupational mobility network, RN = related network. ***, **, * indicate results that are greater than 99.9%, 99%, or 95% of values respectively, which were obtained from a Monte Carlo simulation.

Table S16 shows the average results over 100,000 randomizations of the results in Table S15.

	OMN	RN	mixed 50/50
2020-2034	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
2034-2038	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Consistent growth (alternative)	-0.002 (0.01)	-0.002 (0.00)	-0.002 (0.01)
Temporary growth (alternative)	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)
Consistent decline (alternative)	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01))

Table S16: **Average assortativity of the randomized shock relative to employment on different occupation networks.** OMN = occupational mobility network. OMN = occupational mobility network, RN = related network. Standard deviations obtained from monte carlo simulation in brackets.

D.5 Beyond green and grown occupations

Our measure of dividing the occupational demand patterns into 'Consistent growth', 'Temporary growth', and 'Consistent decline' is related to the *green jobs* literature, which aims to classify which occupations or jobs more generally can be deemed green or brown. These measures lead to a distinction between green and brown jobs, sometimes with sub-classifications of green jobs (Bowen et al., 2018; Dierdorff et al., 2009; Vona et al., 2018; Peters, 2014). Green occupations are generally regarded as those that will see a growth in demand due to the green transition, while brown occupations will see a decrease in demand due to the phase out of fossil fuels. For example, Dierdorff et al. (2009) classify occupations into three green classes: *Green increased demand* for occupations whose demand increases when pursuing green policies, *Green new & emerging* occupations, and *Green enhanced skills* occupations that may require significant modifications to their tasks and skill requirements due to greening the economy.

In total, Vona et al. (2021) indicate five ways to classify green occupations. Besides the binary approach (e.g., the aforementioned Dierdorff et al. (2009)) and the task approach from Vona et al. (2018), one can use green job vacancies, information on green technologies and productions, and the pollution content of jobs to define green occupations.

In Table S17, we compare our trajectory-based occupational classification with both O*NET's green occupational typology and Vona et al. (2018)'s classification of *Brown* occupations, which includes occupations that are overrepresented in polluting industries. We find that *Consistent growth* occupations correlate with *Green new & emerging* occupations and that *Consistent decline* occupations correlate with *Brown* occupations. Interestingly, *Temporary growth* occupations correlates both with *Green increased demand* occupations and *Brown* occupations. Some industries that (Vona et al., 2018) deem *polluting* are also important for producing renewable energy products, such as the "Fabricated Metal Product Manufacturing" industry for wind turbine manufacturing.

	Consist. decline	Consist. growth	Temp. growth	Green enhanced skills	Green new & emerging	Green increased demand	Brown
Consistent decline	1.0***	-0.0	-0.1	0.0	0.0	-0.0	0.3***
Consistent growth	-0.0	1.0***	-0.0	-0.0	0.2***	0.1	0.0
Temporary growth	-0.1	-0.0	1.0***	0.1	0.0	0.3***	0.3***
Green Enhanced Skills	0.0	-0.0	0.1	1.0***	-0.1	-0.1*	-0.0
Green New & Emerging	0.0	0.2***	0.0	-0.1	1.0***	-0.1	-0.1
Green Increased Demand	-0.0	0.1	0.3***	-0.1*	-0.1	1.0***	0.0
Brown	0.3***	0.0	0.3***	-0.0	-0.1	0.0	1.0***

Table S17: **Pearson correlation coefficient between different occupational classifications**. Included are our trajectory-based occupational typology, the occupational classification of different types of green jobs by O*NET (Dierdorff et al., 2009), and the classification of brown jobs by Vona et al. (2018).

D.6 Sensitivity analysis

We test the sensitivity of our results to eight topics with specific data inputs and modeling choices: 1) The 'supply and use' table base years used in Section B.5; 2) the capex cost vectors of Section C.3; 3) the opex literature weights of Section C.3; 4) the T&D cost in Section B.2; 5) the number of years over which we perform the cost smoothing as explained in the Experimental procedures; 6) the employment per occupation-industry pair of Section A.3; 7) the ATB cost curves per technology as mentioned in Section C.1; and 8) the assumptions on import and exports. We also apply additional stress tests that show the robustness of our methodology to extreme cases. We explain each of the separate items in more detail below, and Table S18 gives an overview of each item, the relevant methodology section, and the sensitivity analysis approach and values.

Base year supply and use tables The A matrix in Eq. (7) and beyond is the domestic input-output table, the basis of which are the 2018 'supply and use' tables

	First relevant equations or sections	**Sensitivity analysis approach**	**Default**	**Values in sensitivity analysis**
1) Base year supply and use tables	Eq. (7)	Alternative years	2018	2015 2016 2017 2019
2) Capex cost vectors	Eq. (11)	Add noise	No noise	30 runs with all values multiplied by random normal noise, and re-normalized to sum to unity
3) Opex literature weights	Section B.6	Add noise	No noise	30 runs with all values multiplied by random normal noise, and re-normalized to sum to unity
4a) T&D cost per MW-mile	Eq. (24)	Min / max literature value	1,433 (2018-USD)	932 (2018-USD) (min) 3,624 (2018-USD) (max)
4b) T&D cost factor for three times more powerful lines	Eq. (24)	plus-minus 25%	1.37	1.0275 1.7125
4c) T&D construction occupational breakdown	B matrix in Eq. (23)	More sectoral detail	NAICS 23	NAICS 23713
4d) T&D Opex	Eq. (25)	plus-minus 25%	1.37	1.0275 1.7125
5) Number of years of cost smoothing	Experimental procedures	Alternative values	3	1 (no smoothing) 5
6) Employment per occupation-industry pair	Eq. (16)	Standard deviation	Point estimate	Point estimate + standard deviation Point estimate - standard deviation
7) Technology cost curves	Eqs. 1-5	Alternative projections from NREL's ATB	Moderate	Advanced Conservative Pro-fossil fuel (pro-ff) Pro-renewables (pro-re)
8) Imports and exports	Eq. (9), Section B.5	Alternative stylized projections	constant exports values, constant import fraction of demand	Increasing solar and wind exports Decreasing (direct) imports Increasing (direct) imports
Stress test	-	Extreme scenarios	-	Zero new solar and wind Double solar and wind generation

Table S18: **Sensitivity analysis overview.**

provided by BEA as explained in Section B.5. In our sensitivity analysis we also use the ‘supply and use’ tables from 2015, 2016, 2017, and 2019. Fig. S16 shows the difference in technical coefficients of the domestic IO table after performing the electricity sector disaggregation procedure of Section B.6.1. There is some diffusion visible, but we find that a different choice of IO base year has only a limited impact on our results.

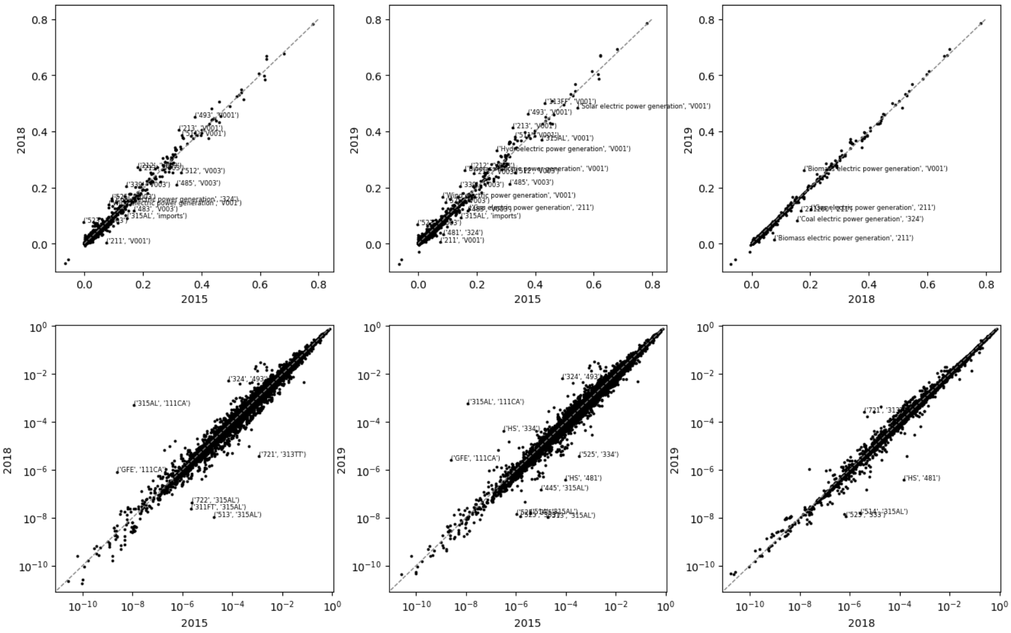


Figure S16: **Scatter plot of technical coefficients for different IO base years**. From left to right: 2015 vs 2018, 2015 vs 2019, and 2018 vs 2019. Bottom row log-log plots correspond to the linear plots from the top row. Any changes of more than 5 percentage points (top) or 50x (bottom) are labeled.

Capex cost vectors We translate capex cost per technology into spending on final demand per industry in Eq. (11). The translation from technology i to the IO industries is done using capex cost vector K_i^{capex}, where each element K_{ij}^{capex} is the fraction of technology i capex that is spent on industry j. We initialize the K_{ij}^{capex} using previous literature estimates. The cost vectors we use in our main analysis are shown in Table S3.

For our sensitivity analysis, we use random noise to generate alternative cost vectors around the estimates used to produce the main results:

$$K_{ij}^{\text{SAcapex}} = \max(0, 1 + \epsilon_{ij}^{K}) K_{ij}^{\text{capex}} \beta_i, \tag{46}$$

where $\beta_i = \frac{1}{\sum_j \max(0,1+\epsilon_{ij}^{K}) K_{ij}^{\text{capex}}}$ is the normalization constant such that $\sum_j K_{ij}^{\text{SAcapex}} = 1$, and the maximum operator makes sure no value is negative. We draw $\epsilon_{ij}^{K} \sim \mathcal{N}(\mu, \sigma^2)$ from a normal distribution with $\sigma = 0.5$. We do this 30 times, which we show in Fig. S20, and take the mean and standard deviation of all 30 runs to show the results in Figs. S18 and S19. This has a minor effect on the results.

Opex cost vectors In Section B.6 we discuss how we disaggregate the IO table using literature estimates of their production recipes.

Analogously to the capex cost vectors, we apply Eq. (46) to the electricity sector opex cost vectors B from the literature of Table S5 to create additional opex cost vectors

$$B_{ij}^{\text{SA}} = \max(0, 1 + \epsilon_{ij}^{B}) B_{ij} \beta_i, \tag{47}$$

where $\beta_i = \frac{1}{\sum_j \max(0,1+\epsilon_{ij}^{B}) B_{ij}}$ is the normalization constant such that still $\sum_j B_{ij}^{\text{SA}} = 1$. We draw $\epsilon_{ij}^{B} \sim \mathcal{N}(\mu, \sigma^2)$ from a normal distribution with $\sigma = 0.5$. This has a minor effect on the results.

T&D cost In Eq. (24), we assume transmission grid costs 1,433 2018-USD / MW-mile. A different publication, Brinkman et al. (2021), puts the cost between 900 (932 2018-USD) and 3,500 USD (3,624 2018-USD) per MW-mile. We use those two numbers as a lower and upper bound on T&D line cost. Secondly, in Eq. (24), we assume three times more powerful lines can be installed for 1.37 times the cost. In the sensitivity analysis, we change this value by 25% to 1.0275 and 1.7125. This can impact the results, and line cost uncertainty translates to one of the largest uncertainties on the peak demand for workers in 2034 (see Fig. S20a).

T&D construction occupational breakdown To keep our methodological framework internally consistent, we do not always use the most detailed industry-level occupational breakdown available in BLS data. Specifically, BLS has occupational data for NAICS sector 23713 (Power and Communication Line and Related Structures Construction). We test the sensitivity of our results to the choice of industry when calculating the occupational demand for the construction part of T&D capex, which in the base case is calculated using the more general NAICS sector 23 (Construction).

Specifically, we update the construction sector part of the B matrix of Eq. (23) and use that one for the construction part of the T&D capex. This has a small effect on the results and mainly affects Electrical power-line installers.

T&D opex In Eq. (25), we use a factor of 1.37 to calculate the opex needs to maintain 3 times as powerful lines, analogous to the capex calculation. In the sensitivity analysis, we increase and decrease this value by 25%, i.e. 1.0275 and 1.7125.

This parameter has a small effect on most occupations and the peak value in 2034 but a large effect on specialized occupations such as Electrical power-line installers and repairers, as well as the steady-state level of employment post-2038.

Number of years of cost smoothing To make the investment flows less erratic, we smooth them using a 3-year moving window. We change this by using a 5-year moving window or by applying no smoothing. More smoothing results in a less peaky and erratic trajectory, as can be seen in Fig. S19.

Employment per occupation-industry pair In Eq. (16), we use M_{ij}, the number of workers in occupation i in industry j per million output. We calculate M_{ij} in Eq. (23) using B_{ij}, the total number of workers in occupation i employed in industry j in 2018. This data is from BLS. BLS also provides Percent relative standard error (PRSE) per B_{ij}. We construct two additional versions $B_{ij}^{+\sigma} = B_{ij} + \sigma_{ij}^{B}$ and $B_{ij}^{-\sigma} = B_{ij} - \sigma_{ij}^{B}$ to test our results sensitivity to this data input. This affects some smaller occupation-industry pairs that are important to the transition most, such as wind turbine service technicians.

ATB cost curves Our baseline scenarios use the *moderate* ATB unit cost curves per technology as provided by NREL. These unit costs are used in Eqs. (1)-(5) to translate electricity capacity and generation to capex and opex.

We will test our model for sensitivity by employing NREL's other unit cost trajectories: the *conservative* and *advances* scenario. In addition, we add pro-fossil fuel (pro-ff) and pro-renewables (pro-re) cost curves, which are combinations of the conservative and advanced cost curves. In the pro-ff (pro-re), we take the advanced (conservative) estimate for fossil fuel technologies and the conservative (advanced) estimates for all renewable technologies and battery storage. The uncertainty in cost curves is one of the larger uncertainty factors for the peak worker demand in 2034.

Imports and exports In the baseline, we assume exports per sector remain constant over time and that the direct import fraction (m_j in Eq.(9) and SM Table S2) is fixed. We test the sensitivity of these assumptions by using other, stylized projections for direct imports and exports of solar and wind electricity generation products.

We explore four alternative scenarios (see also Fig. S17):

1. Increasing solar and wind exports. To simulate increasing exports, we increase the amount of spending on solar and wind capex products in the *95% by 2035* scenario in steps, starting from 2030. Specifically, we increase the spending on selected capex parts by 10% of 2030 production for 2030-2034, 30% of 2030 production for 2035-2039, and 50% for 2040 and later. In practical terms, this

means replacing Eq. (10) with

$$f_{i,t}^{\text{capex},j} = C_{j,t}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}} + \zeta_t \rho_i C_{j,2030}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}}, \tag{48}$$

for $j \in \{solar, wind\}$, and Eq. (10) otherwise. $\zeta_t = 0$ for $t < 2030$, 0.1 for $2030 \leq t < 2035$, 0.3 for $2035 \leq t < 2040$, and 0.5 for $2040 \leq t$. ρ_i is an indicator function that is equal to 1 if industry i is an industry producing exportable goods. For example, products from the Machinery industry are easy to export, but those from the Construction sector are not. We make a considered decision to include the following industries as producing exportable goods or services, and include transportation services that would be required for the export of these goods: $\rho_i = 1$ for i in 'Forestry, fishing, and related activities', 'Oil and gas extraction', 'Mining, except oil and gas', 'Support activities for mining', 'Petroleum and coal products', 'Chemical products', 'Plastic and rubber products', 'Nonmetallic mineral products', 'Fabricated metal products', 'Machinery', 'Computer and electronic products', Electrical equipment, appliances, and components', 'Rail transportation', 'Truck transportation', 'Pipeline transportation', 'Miscellaneous professional, scientific, and technical services', and 'Management of companies and enterprises'.

To put this into perspective, we can look at the current US export data on solar and wind turbines. This data is not easy to find, because export data is often not detailed enough to specify if products are for renewable energy use only. For example, important subcomponents such as inverters can be used for many purposes, and product classifications are often not granular enough to tell green energy technology apart from other technologies. But some products are easier to identify. We find that the US exported 112 million USD worth of four products specific to solar PV cells and solar PV generators.[36] In Fig. S5,

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[36] Photosensitive devices; unassembled photovoltaic cells (HS code 854142). Photosensitive devices; assembled photovoltaic modules/panels (HS code 8541423). Electric generators; photovoltaic

we find that PV cells represent 61% of solar system capex, the rest being BOS hardware and the inverter. For each, we assume the US exports these goods proportional to the other PV-related exports, which brings the total to 184 million USD.

For wind energy, we find that the US exported two wind energy products (Wind-powered electric generators and Iron or steel towers)[37] for 199 million USD in 2022. NREL indicates that the generator represents 9.3% of total wind turbine capex, and the generator plus tower represents 24.5% (Fingersh et al., 2006; Stehly et al., 2022). The Wind-powered electric generator exports likely also contain other products in the wind-powered drive train, and the 9.3% is likely an underestimate. Similarly, Iron and steel towers know many applications, not just wind turbines. But if we assume the US exports other products (gearbox, blades, bearings, mainframe, etc.) proportional to the wind-powered electric generator exports with or without the iron or steel towers, that would bring total wind turbine exports in 2022 to 812 million to 2.1 billion, respectively.

This brings the total exports of solar and wind products to 996–2,284 million. In the *increasing exports* scenario, this translates to an export increase of 85–195% in 2030, 250–570% in 2035 and 416–950% in 2040.

2. Decreasing (direct) imports. We decrease the direct imports in the *95% by 2035* scenario in steps, by adjusting the import vector m in Eq. (9) to

$$\widehat{K}_{ij}^{\text{capex}} = (1 - \tau_t m_j) K_{ij}^{\text{capex}}, \tag{49}$$

where the *direct imports fraction multiplier* $\tau_t = 1$ for $t < 2030$, 0.9 for $2030 \leq$

DC generators, of an output exceeding 50W (HS code 850172). Electric generators; photovoltaic DC generators, of an output not exceeding 50W (850171). All export data for 2022 from the Observatory of Economic Complexity (https://oec.world/en/profile/).

[37] HS codes 850231 and 730820, respectively.

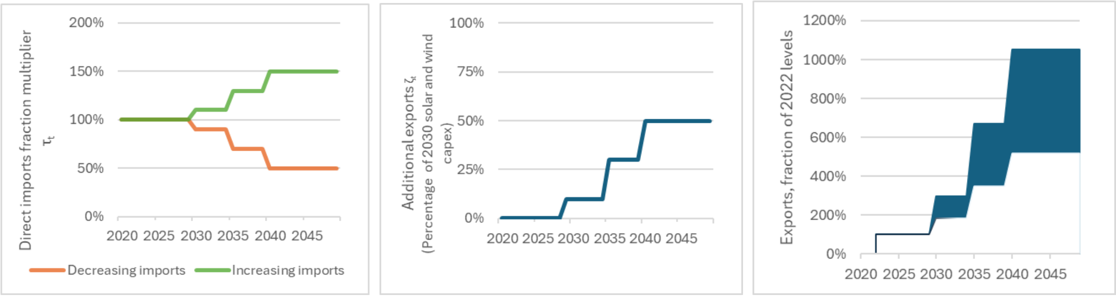
$t < 2035$, 0.7 for $2035 \leq t < 2040$, and 0.5 for $2040 \leq t$.

3. Increasing exports and decreasing (direct) imports. This combines items 1 and 2 above

4. Increasing (direct) imports. This simulates the opposite effect of item 2 above by increasing direct imports in the *95% by 2035* scenario in steps, via import vector m as we replace Eq. (9) with

$$\widehat{K}_{ij}^{\text{capex}} = (1 - \max(1, \tau_t m_j))K_{ij}^{\text{capex}}, \tag{50}$$

where $\tau_t = 1$ for $t < 2030$, 1.1 for $2030 \leq t < 2035$, 1.3 for $2035 \leq t < 2040$, and 1.5 for $2040 \leq t$. The max() function ensures the import fraction remains bounded by 1 (i.e., 100% imported) from above.



(a) Imports

(b) Increasing exports (fraction of additional 2030 production)

(c) Increasing exports (compared to 2022 exports)

Figure S17: **Stylized scenarios for imports and exports.** a) The direct import fraction multiplier τ_t over time, which is used to change the direct import fractions over time in the scenarios with decreasing or increasing direct exports in Eqs. (49) and (50), respectively; b) the additional exports ζ_t over time, which governs the level of exports in the scenario with increasing exports as per Eq. (48); c) the additional exports over time as fraction of 2022 exports, as explained in the text; the shaded area represents the uncertainty.

Higher export and lower import levels leads to higher job numbers, especially for manufacturing occupations, and in particular after 2040 when the divergence from the *reference* scenario is greatest. Vice versa, higher levels of imports lead to lower demand for workers. The import/export uncertainty is one of the largest causes of uncertainty for the estimated worker demand in 2045 (see Fig. S20b).

Stress test Finally, we stress-test our framework with two extreme scenarios: The *Zero new solar and wind* scenario is the same as our base case but with new solar and wind generation and capacity artificially set to zero. In the *Double generation solar and wind* scenario, we have artificially doubled the generation for solar and wind while keeping everything else the same as the base case.

These scenarios should not be seen as part of the sensitivity analysis but rather to check the robustness of our framework and aid interpretation. For example, we find that the *Zero new solar and wind* scenario leads to flat demand for Solar PV installers and lower demand for some construction trades. Similarly, the *Double generation solar and wind* scenario leads to a doubling of the demand for Wind turbine service technicians.

We include their results in the figures in this section but not in the main text.

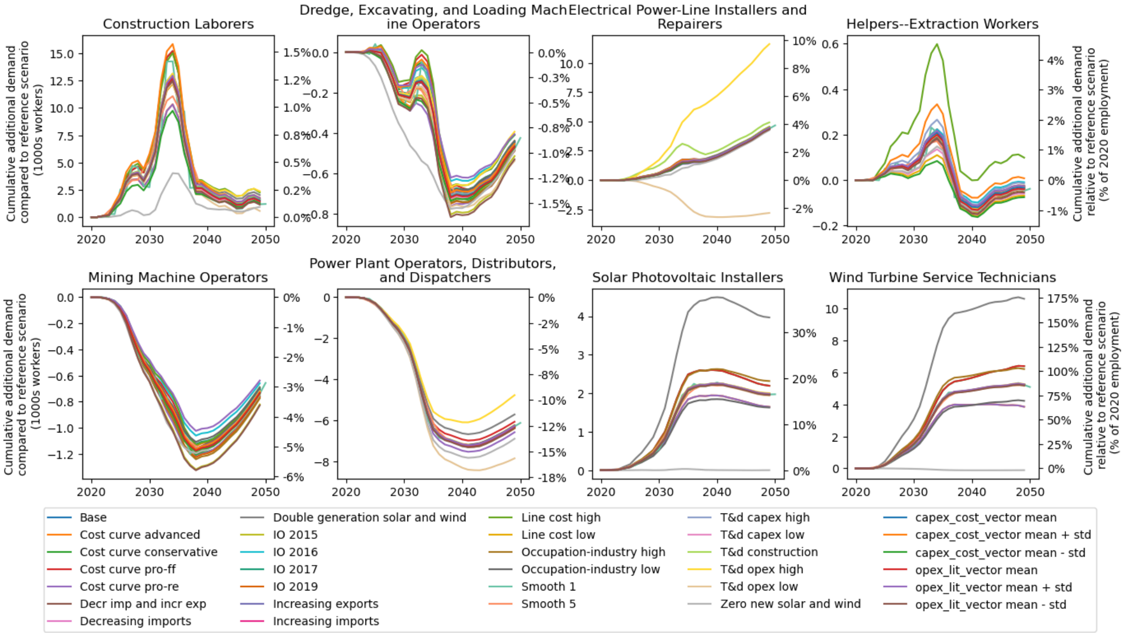


Figure S18: **Sensitivity of occupation trajectories over time of selected occupations.**

D.6.1 Impact of sensitivity analysis on temporal profiles

Fig. S18 shows the impact of the parameter sensitivity on trajectories of individual occupations. What item has the most impact differs per occupation. Electrical Power-Line Installers and Repairers have the most uncertainty of the selected occu-

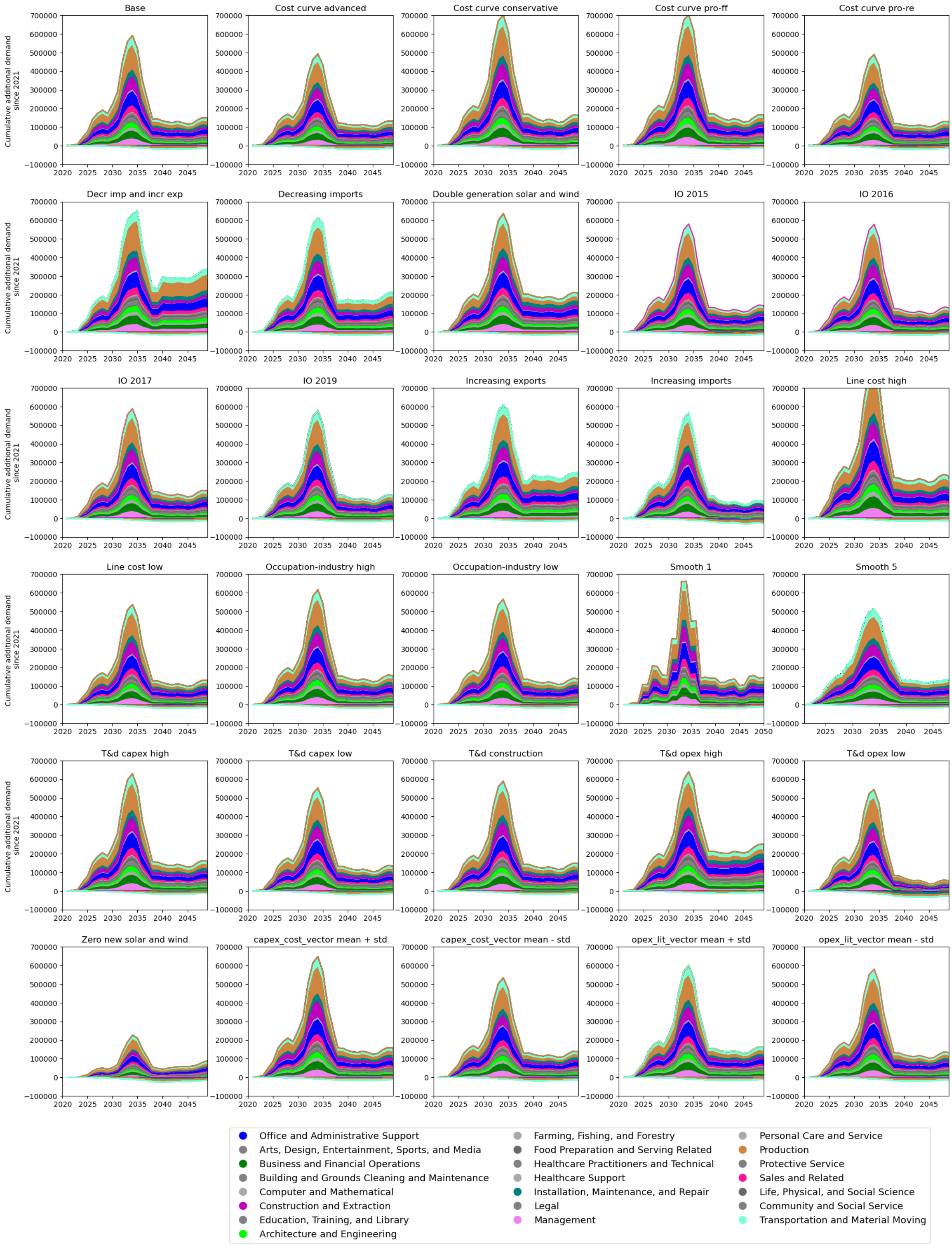


Figure S19: **Cumulative sum of net occupational demand changes over time.** Each plot changes one parameter of the sensitivity analysis. Top left figure reproduces the right-hand side figure of Fig. 2.

pations and are impacted mainly by T&D opex changes. Solar PV installers and

Wind Turbine Technicians have different trajectories that depend mostly on the assumption of energy cost reductions over time, as well as measurement errors by BLS, as these occupations are still relatively new and small.

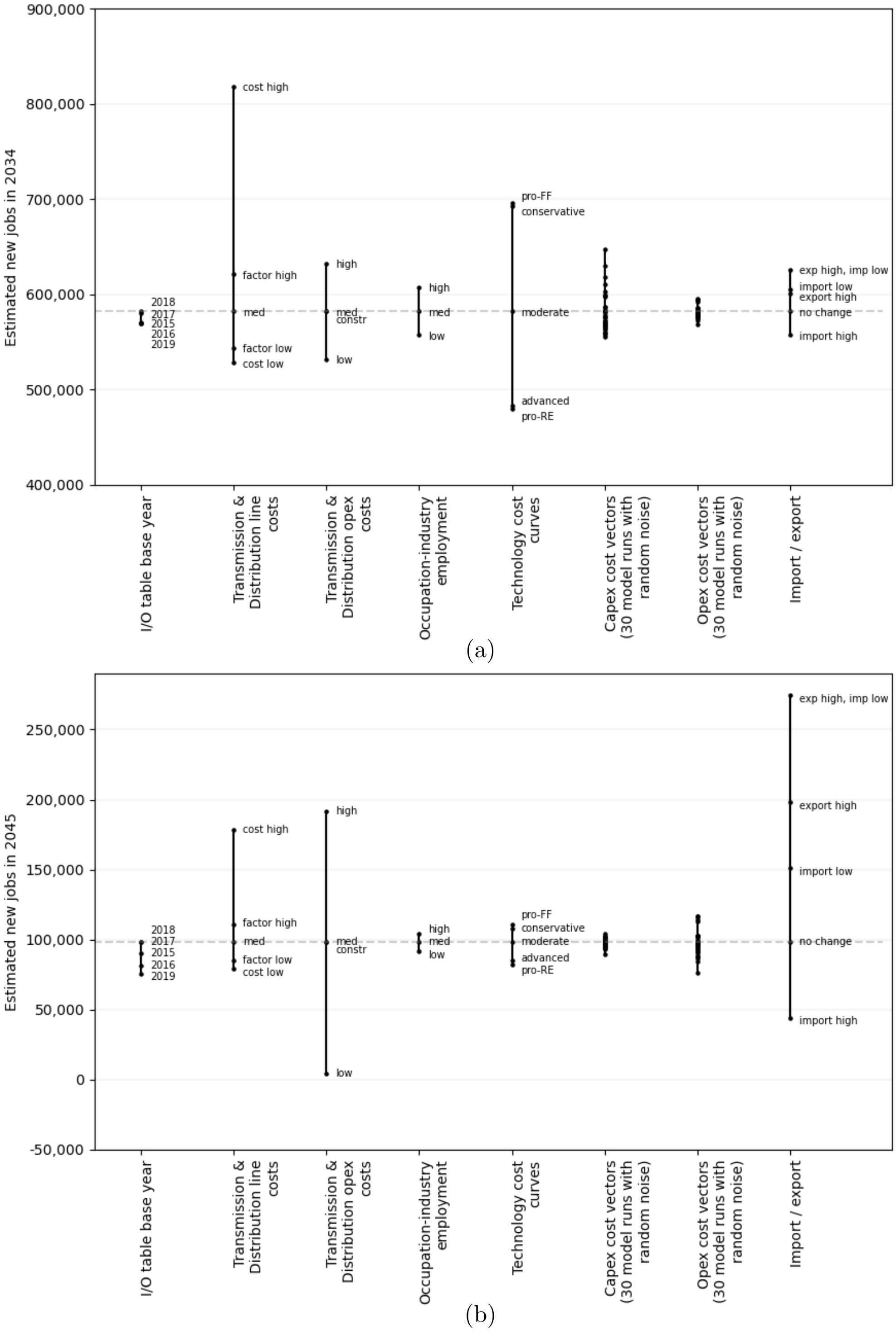


Figure S20: **Results from a sensitivity analysis on estimated net additional jobs from changes to key variables and components used in the modeling.** a) 2034 during the peak; b) 2045 during the steady state phase

Fig. S19 shows the aggregated demand for workers of all occupations in a stacked bar plot. The top left sub-figure reproduces the right-hand side figure of Fig. 2. While the overall shape of the figures is very similar in all cases, with a peak at 2034 and a relatively steady state after 2038, the size of the peak and steady-state employment can differ. Fig. S20 shows the net employment demand changes relative to the *reference* scenario for the peak in 2034, and the steady state phase in 2045.

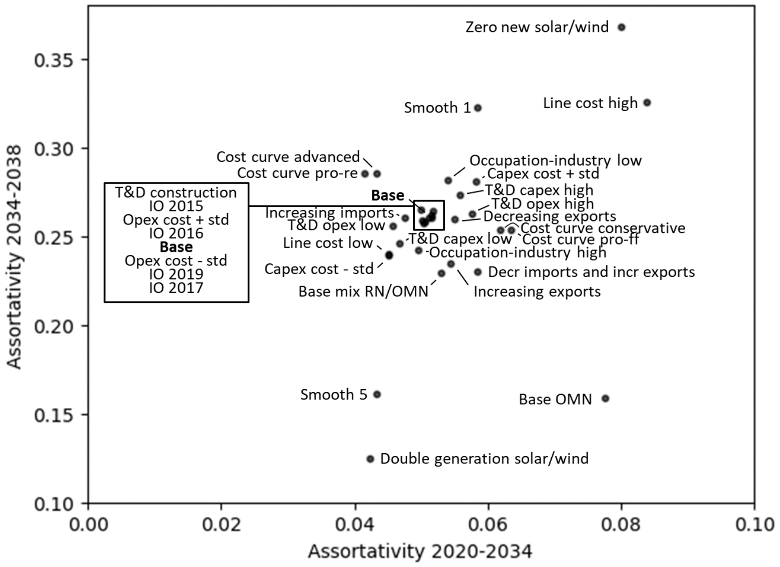


Figure S21: **Sensitivity analysis of assortativity analysis of scale-up (x axis) and scale-down (y-axis) phases**. The value for Base corresponds to the scale-up and scale-down values in Table 1. The mix RN/OMN = 50/50 mix of the related network (RN) and empirical occupational mobility network (OMN) (see Section B.9)

Higher line costs, more conservative cost curves, and the lack of a smoothing window lead to much higher net labor demand in 2034. The latter also leads to much more erratic occupational demand profiles. Import and export trajectories, opex T&D employment factors, and transmission line costs have the largest impact on 2045 employment. The large effects of the import and export scenarios in 2045 compared to the peak in 2034 are because the differences with the baseline grow over time.

D.6.2 Assortativity analysis

For each of the sensitivity analysis items, Fig. S21 shows the assortativity of shocks relative to employment on the combined network before and after the peak during the transition, as a further robustness check on Table 1. We also included the assortativity calculation of the base assumptions using the empirical occupational mobility network (OMN) and the mixed network (as defined in Section B.9). For more results on the assortativity levels of the different networks, see Section D.4.3.

We can see that the assortativity levels for the 2034-2038 period all deviate by less than 25% from the Base estimate, except for 5-year smoothing and the assortativity using the occupational mobility network (OMN), which moves the assortativity to almost 40% lower than the base estimate. For the 2020–2034 period, we find that the assortativity values for OMN and high line cost are more than 25% removed from the base estimate, respectively 40% and 55% higher.

The two sense checks of *Zero new solar/wind* and *Double generation of solar/wind* are not variations on assumptions but extreme cases to test the framework and should not be included when considering the robustness of our framework.

Most of the assumptions move assortativity up or down for both time periods, but two do not. Using more ambitious (*advanced*) learning rates on cost curves leads to lower assortativity in the scale-up phase (2020–2034) but higher assortativity in the scale-down phase (2034–2038). The occupational mobility network, vice versa, has higher assortativity for the scale-up phase and lower for the scale-down phase.

E Full list of industries and occupations in this study

Table S19 lists all industries and their aggregated industry classification used in this study. This represents the full US economy, except for the US government defense sector, which is left out. Table S20 lists all occupations used in this study and is attached as a separate Excel table. Military occupations are not included.

NAICS	Industry name	Code	Aggregated industry name
111CA	Farms	11	Agriculture, Forestry, Fishing and Hunting
113FF	Forestry, fishing, and related activities	11	Agriculture, Forestry, Fishing and Hunting
211	Oil and gas extraction	21	Mining
212	Mining, except oil and gas	21	Mining
213	Support activities for mining	21	Mining
221111	Hydroelectric Power Generation	22	Utilities
221112a	Fossil Fuel Electric Power Generation: coal	22	Utilities
221112b	Fossil Fuel Electric Power Generation: gas	22	Utilities
221113	Nuclear Electric Power Generation	22	Utilities
221114	Solar Electric Power Generation	22	Utilities
221115	Wind Electric Power Generation	22	Utilities
221116	Geothermal Electric Power Generation	22	Utilities
221117	Biomass Electric Power Generation	22	Utilities
221118	Other Electric Power Generation	22	Utilities
221121	Electric Bulk Power Transmission and Control	22	Utilities
221122	Electric Power Distribution	22	Utilities
221210	Natural Gas Distribution	22	Utilities
2213	Water, Sewage and Other Systems	22	Utilities
23	Construction	23	Construction
311FT	Food and beverage and tobacco products	30	Manufacturing
313TT	Textile mills and textile product mills	30	Manufacturing
315AL	Apparel and leather and allied products	30	Manufacturing
321	Wood products	30	Manufacturing
322	Paper products	30	Manufacturing
323	Printing and related support activities	30	Manufacturing
324	Petroleum and coal products	30	Manufacturing
325	Chemical products	30	Manufacturing
326	Plastics and rubber products	30	Manufacturing
327	Nonmetallic mineral products	30	Manufacturing
331	Primary metals	30	Manufacturing
332	Fabricated metal products	30	Manufacturing
333	Machinery	30	Manufacturing
334	Computer and electronic products	30	Manufacturing
335	Electrical equipment, appliances, and components	30	Manufacturing
3361MV	Motor vehicles, bodies and trailers, and parts	30	Manufacturing
3364OT	Other transportation equipment	30	Manufacturing
337	Furniture and related products	30	Manufacturing
339	Miscellaneous manufacturing	30	Manufacturing
42	Wholesale trade	42	Wholesale Trade
441	Motor vehicle and parts dealers	4A	Retail Trade
445	Food and beverage stores	4A	Retail Trade
452	General merchandise stores	4A	Retail Trade
4A0	Other retail	4A	Retail Trade
481	Air transportation	4B	Transportation
482	Rail transportation	4B	Transportation
483	Water transportation	4B	Transportation
484	Truck transportation	4B	Transportation
485	Transit and ground passenger transportation	4B	Transportation
486	Pipeline transportation	4B	Transportation
487OS	Other transportation and support activities	4B	Transportation
493	Warehousing and storage	4B	Transportation
511	Publishing industries, except internet (includes software)	51	Information
512	Motion picture and sound recording industries	51	Information
513	Broadcasting and telecommunications	51	Information
514	Data processing, internet publishing, and other information services	51	Information
521CI	Federal Reserve banks, credit intermediation, and related activities	52	Finance and Insurance
523	Securities, commodity contracts, and investments	52	Finance and Insurance
524	Insurance carriers and related activities	52	Finance and Insurance
525	Funds, trusts, and other financial vehicles	52	Finance and Insurance
HS	Housing	RE	Real Estate and Rental and Leasing
ORE	Other real estate	RE	Real Estate and Rental and Leasing
532RL	Rental and leasing services and lessors of intangible assets	RE	Real Estate and Rental and Leasing
5411	Legal services	54	Professional services
5412OP	Miscellaneous professional, scientific, and technical services	54	Professional services
5415	Computer systems design and related services	54	Professional services
55	Management of companies and enterprises	55	Management of Companies and Enterprises
561	Administrative and support services	56	Administrative and Support and Waste Management and Remediation Services
562	Waste management and remediation services	56	Administrative and Support and Waste Management and Remediation Services
61	Educational services	61	Educational Services
621	Ambulatory health care services	62	Health Care and Social Assistance
622	Hospitals	62	Health Care and Social Assistance
623	Nursing and residential care facilities	62	Health Care and Social Assistance
624	Social assistance	62	Health Care and Social Assistance
711AS	Performing arts, spectator sports, museums, and related activities	71	Arts, Entertainment, and Recreation
713	Amusements, gambling, and recreation industries	71	Arts, Entertainment, and Recreation
721	Accommodation	72	Accommodation and Food Services
722	Food services and drinking places	72	Accommodation and Food Services
81	Other services, except government	81	Other Services (except Public Administration)
GFGN	Federal general government (nondefense)	G	Public Administration
GFE	Federal government enterprises	G	Public Administration
GSLG	State and local general government	G	Public Administration
GSLE	State and local government enterprises	G	Public Administration

Table S19: **List of industries used in this study.**

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4 From potatoes to silicon chips: the role of product skill intensity in structural change

Joris Bücker[a,b,*] and Penny Mealy[a,b,c,d]

[a] *Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK*
[b] *Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK*
[c] *Santa Fe Institute, Santa Fe, NM, USA*
[d] *SoDa Labs, Monash Business School, Melbourne, Victoria, Australia*
[*] *Corresponding author: joris.bucker@seh.ox.ac.uk. 14 Anne Greenwood Close, OX4 4DN, Oxford, UK*

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The authors declare no competing interests.

Abstract

While many have stressed the importance of skills, human capital and education for economic development, few have sought to make the direct link between a workforce's skills and the sophistication of their country's exported products. This paper aims to address this gap by introducing new product and country level measures of skill intensity and explores the implications for growth and development. Our main product-level measure, called *product skill intensity*, is based on the educational attainment of workers in occupations in industries that produce the product. Product skill intensity gives an intuitive ranking of both aggregated product categories and more detailed products within categories. More skill-intense products tend to require a wide variety of occupations by skill intensity. Our work makes three contributions to the research on structural change and development. First, our new measures of product skill intensity can help advance other research questions in trade and development studies. Second, we show that the *product space* network of traded products can be divided into a low- and a high-skill part, distinct from its well-studied core-periphery dichotomy. And third, our country-level metrics introduce novel ways to assess countries' ability to apply human capital to diversify their export baskets. Countries – especially those with higher education levels – tend to diversify towards products with a positive *skill distance* from a country's level of education. Together, these contributions advance our understanding of the link between two of the main drivers of development and growth – human capital and structural change.

Keywords Human capital, structural change, skills, economic growth, economic complexity, export diversification

Introduction

Structural change, the shift over time towards producing more *sophisticated* goods, is important for growth and economic development (Kuznets, 1955; Syrquin, 1988; Timmer et al., 2015; Brummitt et al., 2020). Production and export patterns are difficult to change due to their path dependence and thus have a protracted influence on a country's development (Lall, 2000). In general, the production and export of more sophisticated products requires more advanced 'production capabilities', such as infrastructure, technological know-how, and institutions that are conducive to productivity growth and diversification spillovers (Lall, 1992; Hidalgo and Hausmann, 2009). The ability of a country to produce and export sophisticated products can thus be informative of its economic structure and capacity to grow further (Lall et al., 2006; Hausmann et al., 2007; Tacchella et al., 2012).

What makes a product 'sophisticated' in this regard, however, has been an elusive question for decades. Directly measuring sophistication from product characteristics is hard and requires specific domain knowledge or very coarse approximations (Lall, 2000; Rajpal and Guerrero, 2023). To overcome this, researchers have come up with indirect methods to measure product-level sophistication, such as product 'sophistication' (Lall et al., 2006; Bustos and Yıldırım, 2022) or 'complexity' (Hidalgo and Hausmann, 2009; Tacchella et al., 2012). These metrics estimate product-level sophistication *revealed* from export data using mathematical and statistical methods. The assumption is that products that are exported by the same countries have similar levels of complexity and, vice versa, that countries that export the same products are similarly complex. However, the mathematical and statistical methods employed and the relationship between trade data and complexity can be hard to interpret (Mealy et al., 2019; Tacchella et al., 2013).

An intuitive alternative way to think about sophistication is in terms of the skills and educational intensity associated with each product. Learning and innovation are of paramount importance for technological and structural change (Stiglitz and Greenwald, 2014; Arrow, 1962; Rodrik and Stiglitz, 2024). While scholars have stressed the general importance of know-how and learning for growth and development (Arrow, 1962; Mankiw et al., 1992; Hanushek and Woessmann, 2008), granular empirical approaches to measuring such relationships have been lacking (Rodrik, 2004; Blanchard and Willmann, 2016; Hidalgo, 2023; Schetter et al., 2024).

Revisiting drivers of product-level sophistication, Hidalgo (2023) shifted the focus from a wide range of capabilities towards 'knowledge' as the key explanation of production capabilities, due to its non-fungibility and natural explanation of path-dependencies. But the quantitative link between human capital and complexity on the product level remains underexplained and has only recently attracted more attention. For example, Schetter et al. (2024) link export capabilities to the presence or absence of *occupational* capabilities in a country, and Felipe et al. (2024) link educational attainment to the ability to diversify into path-breaking directions. In this study, we provide alternative measures of product-level know-how and explicitly address their link to product and economic complexity.

Our study makes four key contributions through the introduction of four new metrics. First, we introduce *product skill intensity*, which ranks products by their level of embedded know-how. Our measure is calculated using the educational attainment of workers in occupations required to produce the good.[1] Product skill intensity gives an intuitive ranking of products: data processing devices and medicaments score highly, while agricultural products and textiles are assigned low scores. Product skill intensity is moderately correlated with product complexity (PCI, see Hidalgo and Hausmann, 2009), indicating that more complex products are often also more skill intense. We find that products with similar skill intensity are often exported together.

We apply the *product space* methodology (Hidalgo et al., 2007) to show how

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[1] This is, of course, a simplification of reality. Know-how and skills could be acquired in many different ways beyond formal schooling, such as learning-by-doing, apprenticeships, self-study, etc. See Materials and methods for more details.

product skill intensity is related to path dependencies of structural change. Similarly skill-intense products are often exported simultaneously by the same country, and we find that the product space can be split into a high-skill and a low-skill part. Earlier research on the product space found that products in the core of the network are more complex (Hidalgo et al., 2007), but we do not find evidence that more core products are necessarily more skill intense. Reminiscent of the middle-income trap (Felipe et al., 2012), these results indicate that a country could get trapped in the low-skilled exports part of the product space, and that this is not necessarily the periphery but also part of the core.

Second, we introduce *skill variety*, a measure of the heterogeneity in skill intensity required to produce a product. The full process of making a product requires various occupations with different skill sets. We find that more skill-intense products tend to have a larger skill variety. In other words, highly skill-intense products still require a lot of workers in occupations with a low skill intensity as well as workers with a high skill intensity. As countries develop and start producing more skill-intense products, they thus potentially require more social capital (Han et al., 2014) and the ability to manage more intricate 'skill ecosystems' (Neffke, 2019).

Third, we introduce an aggregated measure of *country skill intensity*, based on the product skill intensity of a country's exported products. We find that country skill intensity is correlated with GDP per capita. It is also predictive of future growth, and robust to the inclusion of frequently used explanatory variables. We find that our measure augments rather than confounds *mean years of schooling*, a traditional measure of know-how. This indicates that country skill intensity measures something different than educational attainment per se – increasing a country's skill intensity is about the ability to apply education and skills to produce and export specific products. We also compare our results to the Economic complexity index (ECI) (Hidalgo and Hausmann, 2009) and Fitness (Tacchella et al., 2012), two other widely used measures of country-level export sophistication.

Fourth, we develop a metric called *skill distance*, which measures the difference between a product's skill intensity and a country's mean years of schooling. We show that skill distance is informative of product *appearances* on the extensive margin: new products that a country is able to export competitively tend to be relatively skill intense compared to the county's mean years of schooling. Skill distance can complement *density* by Hidalgo et al. (2007) in this context. The higher a country's educational attainment, the less important density becomes and the more skill distance for explaining diversification paths, echoing results by Felipe et al. (2024) and Schetter et al. (2024).

Relevant literature

Our work is related to the existing literature on human capital and development. We start our literature review by discussing their general relationship and limitations to aggregate approaches. We then show how disaggregated data has been used to investigate the path dependence of development and how this links to skills. Finally, we discuss previous attempts to measure the skill intensity of economic activity, both at the product and country level.

Human capital and development

Human capital accumulation, learning, and the ability to innovate are some of the most important drivers of structural change and contributors to long-term GDP growth and higher living standards (Arrow, 1962; Mankiw et al., 1992; Kremer, 1993; Stiglitz and Greenwald, 2014; Hidalgo, 2023). Some call human capital the single most important factor for determining growth and income (Hanushek and Woessmann, 2008; Blanchard and Olney, 2017). Mincer (1984) summarizes human capital's pre-eminence based on its two-sided effect: it both contributes to production and growth together with physical capital, and to the production of new knowledge and innovations which propel all factors of production. Hanushek and Woessmann (2012) conclude that the empirical cross-country relationship between educational achievement and GDP growth is remarkably strong and stable across choice of model specification, time period, and country sample, although some caution is required when assessing the results (Benos and Zotou, 2014). Jetter and Ramírez-Hassan (2015) find that, out of 36 candidate factors, primary school enrollment was one of only two strong Bayesian determinants of export diversification, together with natural resource share of total output. Both the level of education and change matter: countries with higher levels of education and those with a greater increase in educational attainment saw faster economic growth (Sunde and Vischer, 2015) and a faster rise of industries that are educationally intense (Ciccone and Papaioannou, 2009).

Even though the link between human capital and development is strong, it has proven hard to guide development with this insight alone (Hanushek and Woessmann, 2020). Aggregate measures of human capital and schooling can be hard to compare internationally (Wolff, 2000), and they can miss the path dependence of development (Lall, 2000). Not only education policy is important for human capital development, but also the demand for skills, which is influenced by a country's competitive strengths, industrial makeup (Kruss et al., 2015; Funke and Strulik, 2000), and industrial policy (Stiglitz and Greenwald, 2014; Wood and Ridao-Cano, 1999). Skills and technology go together and have been called the 'twin engines' of growth (Lloyd-Ellis and Roberts, 2002), although the causal relationship is unclear (Lee et al., 2020; Azam, 2017; Teixeira and Queirós, 2016). Kruss et al. (2015) suggest the link between education and development is complex with interactions across multiple levels – global, national, sectoral, and spatial. Moreover, the direction of structural change is not always towards more sophisticated products and further learning spillovers (McMillan and Rodrik, 2011). Kremer (1993) explains how small differences in the education system quality of otherwise identical nations can lead to very different outcomes as countries specialize in simple or complicated products due to compounded differences in quality. This, in turn, can exacerbate the – initially small – human capital outcomes.

Disaggregated data and path dependence

Many of the dynamics described in the previous paragraphs cannot be understood from aggregated data (Lall et al., 2006). Furthermore, aggregated human capital statistics can conceal important changes to the labor force. For example, Blanchard and Willmann (2016) show that, while aggregated education levels are stable, specialization in both low- and high-skill products can hollow out the middle-skill class, creating more inequality within countries, a phenomenon that has been observed in some rich countries including the US. Further disaggregation can be important when the dynamics happen within industries, which happens especially in later stages of development and can be missed if sector-level data is not split into more specialized industries (Kruse et al., 2023).

The need for more detailed data has spawned a lively research field that exploits patterns in detailed country-level trade data and relates those to development outcomes. Collectively, this branch of the literature has become known as *economic complexity*. The existing capabilities of a country can make it easier or harder to acquire further capabilities and export other products. In particular, a country is more likely to become competitive in products that are similar to other products already in a country's existing export basket (Lall et al., 2006; Zaccaria et al., 2014; O'Clery et al., 2021). Hidalgo et al. (2007) formalize this with network science by constructing a network of products called the 'product space' where products are linked if they are often co-exported. They find that *density*, a metric of 'closeness' of a country's export basket to a product, is informative of future diversification pathways. Countries and regions are more likely to start exporting products that are more adjacent to their current export baskets (Bahar et al., 2019; Coniglio et al., 2018), use similar skills (Schetter et al., 2024; Johnson, 2020), or follow naturally from it over time (Zaccaria et al., 2014), although unrelated diversification is also important (Alshamsi et al., 2018). An example by Zaccaria et al. (2014) of products that follow one another over time is the progression from radio broadcast receivers to thermionic valves for transistors to personal computers, which closely tracks part of South Korea's export diversification between 1960 and 2000.

To understand which products are more promising to develop, researchers have come up with product-level metrics of *sophistication* (Lall et al., 2006; Bustos and Yıldırım, 2022) or *complexity* (Hidalgo and Hausmann, 2009; Tacchella et al., 2012), and variations including environmentally friendly 'green' complexity (Mealy et al., 2018). These metrics are not based on product characteristics directly, but rather estimated from export data using mathematical and statistical methods. The assumption is that products that are exported by the same country have similar levels of complexity, and, vice versa, that countries that export the same product are also similarly complex and have the same 'capabilities'. However, the mathematical and statistical methods employed and the relationship between trade data and complexity can be hard to interpret (Mealy et al., 2019; Tacchella et al., 2013).

The complexity measures of products can be aggregated to country-level measures of *sophistication* (Lall et al., 2006), *EXPY* (Hausmann et al., 2007), *economic complexity index* (ECI) (Hidalgo and Hausmann, 2009), *fitness* (Tacchella et al., 2012), or *production ability* (Bustos and Yıldırım, 2022). These measures correlate with countries' GDP per capita and are often also predictive of GDP per capita growth (Hidalgo and Hausmann, 2009; Bustos and Yıldırım, 2022), although less so for low-income countries (Chrid et al., 2021). Cristelli et al. (2017) show that their model using *fitness* outperformed the IMF's WEO model, a complicated econometric model of GDP per capita growth.

In recent years, the focal point of explaining the differences in product- and country-level complexity levels has shifted from a broad set of *capabilities* towards human capital. Originally, Hidalgo and Hausmann (2009) used the language of country capabilities, such as “property rights, regulation, infrastructure, specific labor skills, etc.”. Recently, however, Hidalgo (2023) identified human capital – ‘knowledge’ – as the key capability, due to its non-fungibility and natural explanation of path dependencies, and called economic complexity “a development theory more aligned with work focused on learning rather than capital accumulation”. This follows the expansion of the economic complexity literature towards more explicit measures of knowledge, including technologies using patent data (Petralia et al., 2017; Balland and Rigby, 2017; Antonelli et al., 2022) and specific tasks or skills (Divella et al., 2023). More research on the link between product complexity and human capital has been called for, especially in light of increased automation (Balland et al., 2022).

Sophistication, skill intensity, and development

Building on the previous sections, this section reviews a subset of studies that combine disaggregated data on export sophistication and human capital with development indicators, similar to our study. We first highlight four papers that most overlap in questions and methods with ours and discuss where our approach or results differ. Two papers from the early 2000s, An and Iyigun (2004) and Wörz (2005), look at the effect of the skill intensity of exports on GDP growth. Two more recent studies, Felipe et al. (2024), and Schetter et al. (2024), relate disaggregated human capital indicators to export diversification. However, none of these four papers covers both the skill dimension of product diversification and its impact on GDP per capita growth.

An and Iyigun (2004) calculate the export skill content of 86 countries by taking the average of industry R&D intensity, weighed by its export value. They find that their measure is significant for 5-year GDP growth in a multivariate regression analysis spanning the 1970–1990 period. Similarly, Wörz (2005) track 35 industries[2], grouped into different skill levels, in 45 countries. For the 1981–1997 period, they find a positive effect on growth for countries that export a lot of products produced in medium skill intense industries. They find higher growth for non-OECD countries that specialize in low and medium skill industries and lower growth for those that specialize in high skill industries. The relationship is reversed for OECD countries. These studies focus solely on country-level insights, whereas our work connects country- to product-level skill intensity and diversification trajectories. Additionally, we use more detailed skill data, based on the educational attainment of occupations required in product manufacturing, and span a larger number of countries. Nonetheless, our results on GDP growth are largely consistent with their findings.

Exploring the relationship between human capital and product diversification, Felipe et al. (2024) track the comparative advantage of over 1,200 products for 49 low- and middle-income countries. Their results indicate that countries with high education levels are more successful in developing competitiveness in unrelated products, although these are not necessarily more complex products. Education can thus help with 'path-breaking' diversification. We show that this finding is largely consistent with our results in the Results section. We show that skill distance and density complement each other in explaining variation in export diversification. Furthermore, we show that higher levels of aggregate education in a country make density less important when explaining diversification paths, consistent with Felipe et al. (2024), while it makes skill distance more important. This latter finding contrasts with Felipe et al. (2024), who find no evidence that countries with higher education levels are able to diversify into more complex or skill intense products. The difference may be due to a difference in datasets or methods. In particular, our measure of skill distance is a relative measure specific per country-product pair, whereas they measure the propensity to diversity into products that are more skill

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[2] They also stress (p.137) the special status of oil and coal industries that, while significant in their growth regressions, should not be taken as evidence for skill intensity and growth

intense overall.

A different but related approach is taken by Schetter et al. (2024), who look directly at occupations rather than skills. In their work, individual occupations take a role similar to capabilities in Hidalgo and Hausmann (2009): products require a combination of occupations, and products that introduce ‘new’ occupations to a country can unlock further opportunities by bringing the country closer to its capability requirements. This way, Schetter et al. (2024) create a network of occupational similarity between industries, which is informative of country-level diversification. They also find that countries with more years of schooling are more likely to diversify into products that require occupations with higher educational requirements, which is consistent with our results. Going one step further, we find that skill distance becomes more important and density less important for explaining diversification variation for countries with more educational attainment. Our respective approaches to skill intensity are complementary. While Schetter et al. (2024) look at the extensive margin of occupational needs, our method uses the intensive margin of educational requirements. Both of these can be important to understand the multi-dimensional skill content of industries and products. Indeed, Schetter et al. (2024) find that higher-educated countries tend to diversify more into products that require more skilled occupations.

Other papers have also stressed the interplay between export upgrading and human capital. For example, Ekanayake et al. (2023) find that trade in high-tech goods contributes to growth, mainly because of higher education levels and lower population growth. Combining industry and occupational details, Kruse et al. (2023) find that countries specialize in industries first and in certain occupational classes later during development. Lo Turco and Maggioni (2022) find that seven specific items of knowledge and skills – including physics, electronics and critical thinking – have a rank correlation of more than 0.5 with product complexity. They construct a composite *occupational complexity* measure of these seven items and find that this correlates with the economic growth of US metropolitan areas. Some studies have found that even if more complex exports can be achieved – by leaping over more 'proximate' but low-complex products – insufficient levels of human capital could hamper its contribution to growth (Sheridan, 2014; Anand et al., 2012; Bodman and Le, 2013). Nouira and Saafi (2022) find thresholds for human capital, physical capital, and institutional quality, below which ECI's contribution to growth is negative. Similarly, the model of Costinot (2009) shows that higher competitiveness in more complex industries requires a combination of institutional quality and workers' human capital to be able to succeed (see also Teixeira and Queirós (2016)).

Other existing skill intensity metrics

Many other previous research questions have required researchers to develop skill intensity scores for economic activities. We finish our literature review with an overview of their methods.

Early efforts to quantify the skill level of specific industries include that by Keesing (1965), who computed, as a proxy for skill intensity, the ratio of skilled workers (mainly professional, technical, and managerial workers) over semi-skilled operatives and unskilled laborers for 15 industries. He found evidence for the hypothesis that export skill intensity reflects a country's human capital make-up, which is a stylized fact that is consistent with extensions of the Heckscher-Ohlin (HO) model of international trade (Keesing, 1966). The HO model specifies that a country's export basket reflects its factor endowments. While the original HO model includes capital and labor as the two factors, subsequent efforts to come to terms with the Leontief paradox (Leontief, 1953) led to the disaggregation in the model of the labor factor into multiple factors of different skill levels (e.g., Keesing, 1965; Romalis, 2004; Fukase, 2013).

Later papers on the skill intensity of industries often include similar metrics to Keesing (1965)'s that are based on the ratio of skilled over less-skilled workers. For example, Alvarez (2007) calculates the fraction of white-collar wages to the total wage bill as a proxy for the skill intensity of an industry, and Romalis (2004) uses the fraction of production workers over all workers. But international comparisons of these metrics can be tricky: Anderson et al. (2001) show for Mexico, Canada, and the US that skill intensity measures based on calculating the fraction of production workers over all workers are not a good proxy for skill levels. They conclude that a metric based on educational attainment, such as the mean years of schooling of workers, would be superior. Green et al. (2003) and Hanushek and Woessmann (2008) go further and indicate that, for international comparison of an economy's skill level, standardized skill tests such as the Programme for International Student Assessment (PISA) should really be used. But these can be expensive and often cover only a small fraction of the population: for example, Green et al. (2003) use surveys and interviews that include questions on job entry requirements, how long they had trained for the job, and how long it took to do the job well. Recently, more attention has been focused on surveys that directly measure workers' skills in different countries, such as the World Bank's STEP survey or the OECD's PIAAC, as education or schooling systems can differ across countries (Grundke et al., 2017; Caunedo et al., 2023; Lo Bello et al., 2019). Other skill intensity methods include the manual classification of industries into different skill classes (e.g., Lall, 2000; Wörz, 2005; Falk, 2009), R&D intensity per industry (An and Iyigun, 2004; Falk, 2009), and, less commonly, the fraction of workers with a college degree per industry (Jorgenson et al., 2019). Some researchers use more innovative proxies for skill intensity. For example, Barza et al. (2020) leverage the idea that specialized occupations require combination with other specific occupations to be successful. They deem industries 'knowledge-intensive' when they require a lot of occupations that cannot easily be 'recombined' with other occupations. Felipe et al. (2024) follow the logic of Hausmann et al. (2007)'s PRODY measure in defining a metric of a product's educational intensity by calculating the mean years of schooling over all countries that export a product, weighted by the country's revealed comparative advantage (RCA) in that product. In general, most studies use a single aggregated proxy of human capital, but others have studied the multi-dimensionality of education. For example, primary education completion rates, including basic literacy, can have a distinct effect on growth from the fraction of tertiary educated workers or engineers in society (Wolff, 2000; Hanushek and Woessmann, 2020).

Materials and methods

Our Materials and methods section is structured as follows: we first present our methods in the order they appear in the Results section and then introduce the data sources we use.

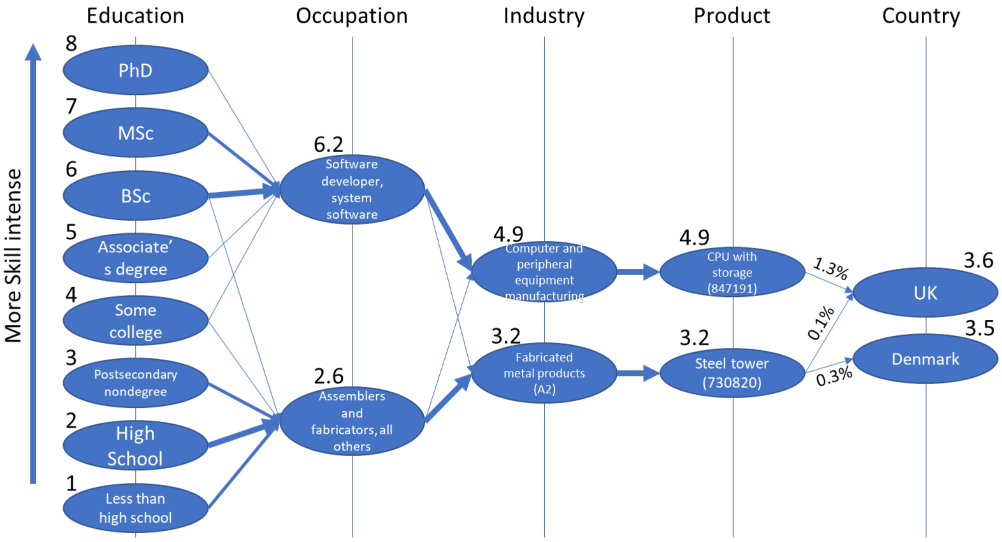

Figure 1: **Relationship between different aggregates of skill intensity.** Country skill intensity is determined by the skill intensity of the education level of workers in occupations in the industries that produce the exported products.

Fig. 1 gives a graphical overview of our main methodology of calculating product and country skill intensity. It shows that, in this work, product skill intensity is linearly related to the workers producing it requiring more formal education. This is, of course, a simplification of how skill acquisition works in reality. Know-how and skills can be acquired in many ways beyond formal schooling, such as learning-by-doing, apprenticeships, self-study, etc. Our measures do not capture this, but we assume that they do capture the *order* of products correctly and that formal education is a good indication of requiring learning more generally.

Skill intensity of occupations, products, and country exports

We define product skill intensity as the average skill intensity of the occupations in industries that produce the product, weighted by their employment. Occupational skill intensity is calculated as the average educational attainment score of its workers in the US. Each of the eight levels of education s in our data is assigned a skill intensity score e_s as per the left side of Fig. 1.[3]

Let n^o_{js} be the number of workers of occupation j that has skill level e_s. The skill intensity of occupation j is then e^o_j, the weighted average skill intensity of its workers:

$$e^o_j = \frac{1}{n^o_j} \sum_s e_s n^o_{js}, \tag{1}$$

where $n^o_j = \sum_s n^o_{js}$ is the total number of workers in occupation j. For a discussion on the values of occupational skill intensity, see Supplementary Materials Section A.

We then use the occupational breakdown per industry to calculate the skill intensity of each industry. Analogously to Eq. (1), the skill intensity e^i_j of industry j is the weighted average of skill intensity of its occupations:

$$e^i_j = \frac{1}{n^i_j} \sum_k e^o_k n_{jk}, \tag{2}$$

where n^i_{jk} is the number of workers employed as occupation k in industry j, and $n^i_j = \sum_k n^i_{jk}$ workers are employed in industry j. Finally, the skill intensity e^p_j of product j is the simple mean of the skill intensity of industries that manufacture

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[3] In Supplementary Materials Section B, we show how the median wage per education level relates to skill intensity.

product j:

$$e_j^p = \frac{1}{|\mathcal{I}_j|} \sum_{k \in \mathcal{I}_j} e_k^i, \tag{3}$$

where $\mathcal{I}_j$ is the set of industries that produce j.

Finally, we calculate country skill intensity as the average product skill intensity of all exported products[4], weighted by their export value. Let x_j^i be the value of exports of product j by country i. We assume that product skill intensity is invariant across countries (i.e., the skill intensity of product j in country i is $e_{ij}^p = e_j^p \ \forall i$). We then define country skill intensity e_i^c of country i as the average product skill intensity of each product that it exports, weighted by export value:

$$e_i^c = \frac{\sum_j x_j^i e_j^p}{\sum_j x_j^i}. \tag{4}$$

Product space and density

The product space is a network where the nodes are products and the edge weight between two products i and j is determined by the proximity ϕ_{ij} between the two products, which is determined by how often i and j are exported competitively by the same country. We calculate proximity following Hidalgo et al. (2007):

$$\phi_{ij} = \min \left\{ P\left(\mathrm{RCA}_i | \mathrm{RCA}_j\right), P\left(\mathrm{RCA}_j | \mathrm{RCA}_i\right) \right\}, \tag{5}$$

where $P\left(\mathrm{RCA}_i | \mathrm{RCA}_j\right)$ is the empirical conditional probability that a country exports product i with RCA>1 given that it exports product j with RCA>1:

$$P\left(\mathrm{RCA}_i | \mathrm{RCA}_j\right) = \frac{\text{Number of countries with an } \mathrm{RCA}_i^c > 1 \text{ and } \mathrm{RCA}_j^c > 1}{\text{Number of countries with } \mathrm{RCA}_j^c > 1}, \tag{6}$$

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[4] Excluding all resource-based products; see Data section of Materials and methods.

and the revealed comparative advantage (RCA_i^c) of product i in country c is the Balassa index:

$$\text{RCA}_i^c = \frac{x_i^c/x^c}{x_i/x}, \tag{7}$$

with x_i^c the export value of product i of country c, and $x^c = \sum_i x_i^c$, $x_i = \sum_c x_i^c$, and $x = \sum_{i,c} x_i^c$. The minimum operator in Eq. (5) prevents rare products from being very close to ubiquitous products and makes the network symmetric. The full product space is a densely connected network. We extract a backbone of the product space, which includes all nodes but only the edges that are part of the maximum spanning tree or those that are larger than threshold r. In the main text, we set $r = \mu + 4\sigma = 0.56$, with μ and σ the mean and standard deviation of ϕ_{ij} over all pairs (i, j). In Supplementary Materials Section F we test the sensitivity of our results for different values of r.

Using the full product space, we calculate the *density* d_{cp}^p of product p in country c to estimate how related product p is to country c (Hidalgo et al., 2007). The density d_{cp}^p is calculated as the fraction of products proximate to product p that are exported competitively ($\text{RCA}_{p'}^c > 1$) by country c:

$$d_{cp}^p = \frac{\sum_{p'|\text{RCA}_{p'}^c>1} \phi_{pp'}}{\sum_{p''} \phi_{pp''}}. \tag{8}$$

Assortativity

We formalize the correlation between the skill intensity of neighboring products in the product space using assortativity. In network science, assortative mixing refers to the inclination of nodes to be connected if they are similar with respect to specific characteristics. In an unweighted network, the assortativity coefficient is equivalent to a Pearson correlation between connected nodes' attributes (Newman, 2018). In our analysis, we use weighted continuous assortativity, which is an extension of the assortativity coefficient for weighted networks and continuous variables (Yuan et al., 2021). This gives the assortativity coefficient $\rho_{G,x}$ between the weighted and undirected network G and continuous node value x as follows:

$$\rho_{G,x} = \frac{\sum_{ij} \left(A_{ij} - \frac{s_i s_j}{W}\right) x_i x_j}{\sum_{ij} \left(s_i \delta_{ij} - \frac{s_i s_j}{W}\right) x_i x_j} \tag{9}$$

where A is the weighted adjacency matrix of G, s_i the strength of node i given by $s_i = \sum_j A_{ij} = \sum_i A_{ij}$, and $W = \sum_{ij} A_{ij}$ the sum of all weights in the network. δ_{ij} is the Kronecker delta that is 1 if $i = j$ and 0 otherwise. For the unweighted case $s_i = k_i$, the degree of node i, and we recover the standard assortativity coefficient from Newman (2018).

Skill variety

We define the *skill variety* v_i of product i as the standard deviation of skill intensity of all occupations associated with product i. We calculate v_i by taking the standard deviation over all occupational skill intensities, weighted by the share of that occupation in product i:

$$v_i = \sqrt{\frac{\sum_k \left(\sum_{j \in \mathcal{I}_i} n_{jk}\right) \left(e_k^o - e_j^p\right)^2}{\sum_k \sum_{j \in \mathcal{I}_i} n_{jk}}}, \tag{10}$$

where $\sum_{j \in \mathcal{I}_i} n_{jk}$ is the number of workers in occupation k in all industries in $\mathcal{I}_i$, the set of industries that produce product i.

Economic Complexity Index (ECI) and Product Complexity Index (PCI)

We define the *capability matrix* M as having elements $M_{cp} = 1$ if $\mathrm{RCA}_p^c > 1$ and 0 otherwise. We use this matrix to calculate the economic complexity index (ECI) and product complexity index (PCI) following Hidalgo and Hausmann (2009); Mealy et al. (2019).

The *diversity* d_c of country c is the number of products for which $\mathrm{RCA}_p^c > 1$: so $d_c = \sum_p M_{cp}$. Vice versa, the *ubiquity* u_p is the number of countries for which $\mathrm{RCA}_p^c > 1$, so $u_p = \sum_c M_{cp}$. Let D be the diagonal matrix with $D_{ii} = d_i$, and U a diagonal matrix with $U_{ii} = u_i$. The ECI is the eigenvector associated with the second largest eigenvalue of the diversity- and ubiquity-weighted similarity matrix $\tilde{M} = D^{-1}MU^{-1}M^T$. The PCI, symmetrically, is the eigenvector associated with the second largest eigenvalue of the matrix $\hat{M} = U^{-1}M^TD^{-1}M$. See Mealy et al. (2019) for details. We standardize both ECI and PCI to zero mean, unit standard deviation variables.

Skill distance

We define the *skill distance* d^s_{cp} between country c and product p as the distance between the normalized mean years of schooling $\hat{s}_c$ of country c and the normalized product skill intensity $\hat{e}^p_p$ of product p, such that

$$d^s_{cp} = \hat{s}_c - \hat{e}^p_p \tag{11}$$

The normalized mean years of schooling and normalized product skill intensities are normalized such that they both have mean 0 and standard deviation 1. A skill distance of 1 between country c and product p then means that the difference in deviation from the mean by years of schooling and product skill intensity is one standard deviation. A positive skill distance indicates a product that is more skill intense compared to other products than a country's mean years of schooling compared to other countries.

We also define an absolute value variety $d^{s,\mathrm{abs}}_{cp}$ called *skill abs distance*:

$$d^{s,\mathrm{abs}}_{cp} = |d^s_{cp}| = |\hat{s}_c - \hat{e}^p_p|, \tag{12}$$

where $|\cdot|$ takes the absolute value. A low value of skill abs distance indicates a product that is ‘close’ to a country’s current education level.

Product appearances on the extensive margin

Product *appearances* in a country are defined by a change in the extensive margin of a country’s competitiveness. A product ‘appears’ in a country if the RCA value of a product changes from below 0.1 to more than 1.0 over time, following O’Clery et al. (2021). More specifically, a product can be present, absent, or undefined in a country: *present* if it is exported with RCA$>$ 1; *absent* if it is exported with RCA$<$ 0.1; undefined for any value in between (0.1 $<$RCA$<$ 1). The appearance happens in the last period when a product was absent before it eventually became present – it can be undefined in any intermediate period.

Formally, we define the *appearance* $J_{cpt} = 1$ if a product p in country c was absent in period t but present in a later period $t^* > t$ and undefined for any and all intermediate periods $\hat{t}$ ($t < \hat{t} < t^*$). We look at appearances between 5-year periods (1995–1999, 2000–2004, 2005–2009, 2010–2014, 2014–2019). A product appears in a 5-year period t ($J_{cpt} = 1$) if the following three conditions hold: 1) $\text{RCA}_{cpt} < 0.1$, 2) $\exists\ t^* > t$ s.t. $\text{RCA}_{cpt^*} > 1$, and 3) $0.1 < \text{RCA}_{cp\hat{t}} < 1\ \forall \hat{t} \in (t, t^*)$. We set $J_{cpt} = 0$ for all product-country pairs that are not present in any period in the dataset. J_{cpt} is undefined – i.e., left out from our analysis – for all other product-country-period tuple. A product that starts appearing in a country in year t is only present in the data for one time ($J_{cpt} = 1$ but $J_{cpt^*} =$ undefined for $t^* \neq t$). To minimize spurious jumps caused by noise, we remove products with less than 5 million USD in global trade.

Our dataset consists of about 2 million country-product pairs, of which 20,000 are appearances.

Data

For the occupation and industry skill intensity calculations, we use data from the US Bureau of Labor Statistics (BLS) on educational attainment per occupation and for an occupational breakdown of workers per industry (Bureau of Labor Statistics, 2021a,b). Product skill intensity is then calculated using the industry-product concordance table from Pierce and Schott (2012), which is available in updated form on their website.[5] This way, we can identify 245 distinct skill intensity levels. One could argue that alternative names that refer to education, such as 'educational intensity', would fit our measure better than 'skill intensity'. However, we disagree, because we use our product-level measure as a stable dimensionless metric that is valid across countries. The US data is used as a proxy for internationally competitive production. While the absolute extent of product skill intensity will differ per country, we believe the relative ranking of products will be more universal. We corroborate this with Brazilian microdata in Supplementary Materials Section G. We find a correlation coefficient between the US and Brazil data of 0.8 for product skill intensity and 0.9 for country skill intensity.

Export data comes from UN Comtrade, as gathered and cleaned by CEPII in the Baci dataset (Gaulier and Zignago, 2010). This consists of over 5,000 products in the HS92 classification and is available from 1995 until 2019 for over 200 countries and territories. The annual data can be noisy. To minimize year-to-year variability caused by noise, we translate all data into 5-year moving averages.

Except for Fig. 2, we exclude from our analysis all resource-based products. Variation in the export of natural resource products is often caused by heterogeneity in the endowment of resource products rather than the development of capabilities to export them (Wörz, 2005). For that reason, we exclude all commodities such as fossil fuels and metals that are in the Chatham House Resource Trade Database

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[5] See `https://faculty.som.yale.edu/peterschott/international-trade-data/`.

(Lee et al., 2012),[6] as well as a further list of coal and petroleum products based on industry-product harmonization.[7] See Supplementary Materials Section C for the difference between our metric of country skill intensity, which excludes resource-based products, and an alternative implementation that uses all exported products.

We also exclude all countries or territories with a population smaller than 1.25 million or a total trade of 1 billion USD or less in 2008, following Albeaik et al. (2017). See Supplementary Materials Section H for the list of all 125 countries we included.

Results

We first present results of product skill intensity, including those related to the product space and skill variety. We then present country-level results on the relationship between country skill intensity and both GDP per capita growth and the dynamics of export diversification.

Product-level insights

Product skill intensity shows heterogeneity both within and between product categories. Fig. 2 shows the skill intensity of all products, grouped by product category (see Table S2 in the Supplementary Materials Section D for the corresponding HS codes, and Table S11 for the full list of products by skill intensity). Some product categories, such as Chemicals & allied materials, and Machinery & electrical products, have a much higher product skill intensity than average, whereas Vegetable products and Textiles score lower. But specific products can be more skill intense.

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[6] In particular, we exclude from our data all products from the Chatham House list in the categories *Fossil fuels*, *Pearls and gemstones*, *Fertilizers*, and *Metals and minerals*.

[7] Specifically, we exclude all products produced by US NAICS industry 324100 (Petroleum and Coal products Manufacturing) and Brazil's CNAE industry 2021-5 (Manufacture of basic petrochemical products). In addition to the Chatham House list, these are the following HS codes: 290110, 290121, 290122, 290123, 290124, 290129, 290220, 290230, 290241, 290242, 290243, 290244, 290290, 290511.

Some processed vegetable products, such as thickeners, and some specialized clothes, such as sports gloves or safety headgear, score high on skill intensity. The most skill-intense products are data processing machinery and some of its parts, such as CPUs; the least skill intense are certain vegetable products such as plant bulbs.

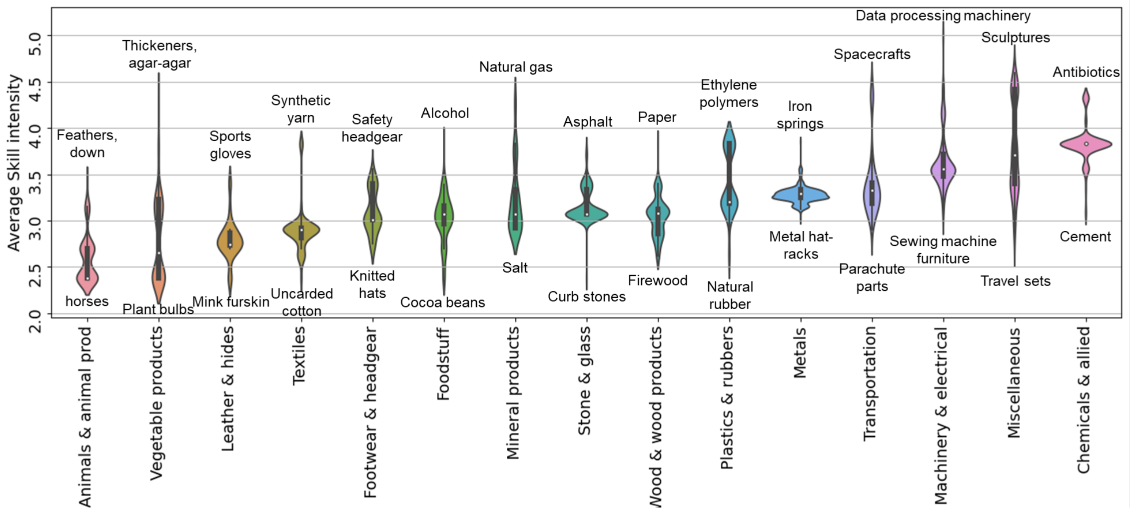
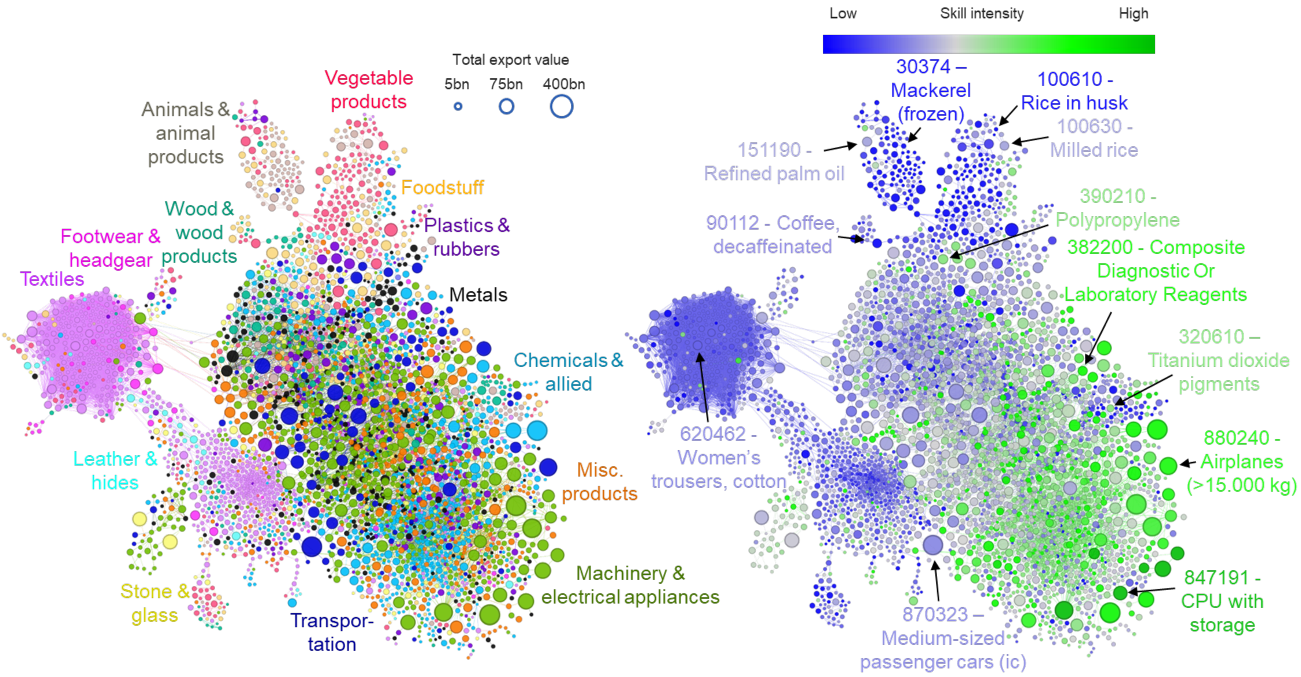


Figure 2: **Product skill intensity within and between product categories**. Examples are given of selected six-digit products in the top and bottom ranking by product skill intensity per product category.

The product space is a network where the nodes are products, and two products are linked if they are often exported by the same country (see Materials and methods for more details). Fig. 3a shows the product space for the 2015–2019 period, with nodes colored by product category. We can see that some product categories group together on the periphery of the product space, such as textiles, vegetable products, and animal products. A denser core consists of multiple product categories, including chemicals and allied products, machinery and electrical appliances, and transportation products.

Fig. 3b plots the product space again, but now with nodes colored by product skill intensity scores. Low and high skill intense products tend to group together in opposite parts of the network. This indicates that products with similar skill intensity are often co-exported together and points to potential polarization in development.



(a) Products colored by product category

(b) Products colored by product skill intensity

Figure 3: **The product space.** Products (nodes) are connected if they are often co-exported. The edge width indicates the strength of the connection, and the node size reflects the total global export value of that product. Only the maximum spanning tree and all other edges with a weight larger than 0.56 (three standard deviations above the mean) are shown. The layout was created using a force-directed algorithm, as implemented in Gephi, modified to minimize overlap, and retouched by hand.

We turn to assortativity, a network science metric, to confirm this hypothesis. Assortativity refers to the tendency of nodes to be connected to other nodes that are like or unlike them in some attribute. An assortativity value of 1 means products are connected only with similarly skill-intense other products – a value of 0 indicates random mixing. In the Materials and methods section, we give an exact definition of the assortativity coefficient. We find a high assortativity coefficient of 0.75, indicating that countries often co-export products that have the same product skill intensity, potentially inhibiting countries with a low skill intensity of exports from moving into more skill-intense products.

In a related but very different setup, Alabdulkareem et al. (2018) also find a strong polarization in the co-occurrence network of skills in occupations. Their 'skillscape' network correlates highly with educational requirements and wages, and their results suggest how skill differences can lead to more workforce polarization. In our work, the polarization of product skill intensity in the product space may be related to the polarization in development pathways associated with the middle-income trap (Agénor, 2017).

In Supplementary Materials Section E, we show that product skill intensity correlates moderately with PCI, with a Pearson correlation coefficient of 0.5. This indicates that, to some extent, more complex products are also more skill intense. But PCI and product skill intensity can also lead to different insights. The product space, for example, has been said in earlier research to be core-periphery, with more complex products in the core (Hidalgo et al., 2007). In contrast, we find no robust relationship between product skill intensity and measures of coreness (see Supplementary Materials Section F). Indeed, the core of Fig. 3b has both areas with low product skill intensity and with high product skill intensity.

Diversity of skill intensity per product

Product skill intensity averages away the diversity of occupations required in product manufacturing. For example, Software developers and Assemblers & fabricators are both involved in the manufacturing of steel towers (see Fig. 1). In Fig. 4, we show how *skill variety*, which is calculated as the standard deviation of skill intensity over all occupations involved in producing a product, correlates with product skill intensity.

For almost all products, skill variety increases linearly with product skill intensity. For example, clothing products tend to have a low skill intensity and a low skill variety. Highly skill intense products, such as medicaments or electrical capacitors, have a much higher skill variety. Very few products buck the linear trend, but one example is the manufacturing of data processing machines and their parts, such as CPUs and other computer components, which is highly skill intense yet requires surprisingly little variation in the skill intensity of its workforce. The strong vertical specialization in the semiconductor and computer industry may contribute to this, with the US capturing more of the high skilled design work than other countries. Another outlier, antiques, is a medium skill intense product with a very low skill variety. Antiques are special products – they are not manufactured but rather acquired, collected, and sold by an apparently relatively homogeneous workforce of medium-skilled workers.

The strong linear relationship between product skill intensity and skill variety indicates that combining workers of different levels of skill intensity becomes more important as countries develop and export more skill-intense products. This relates to the idea of skill complementarities (Neffke, 2019), and potentially requires firms to enhance their social capital (Han et al., 2014) to overcome coordination challenges when starting to produce of more skill-intense products.

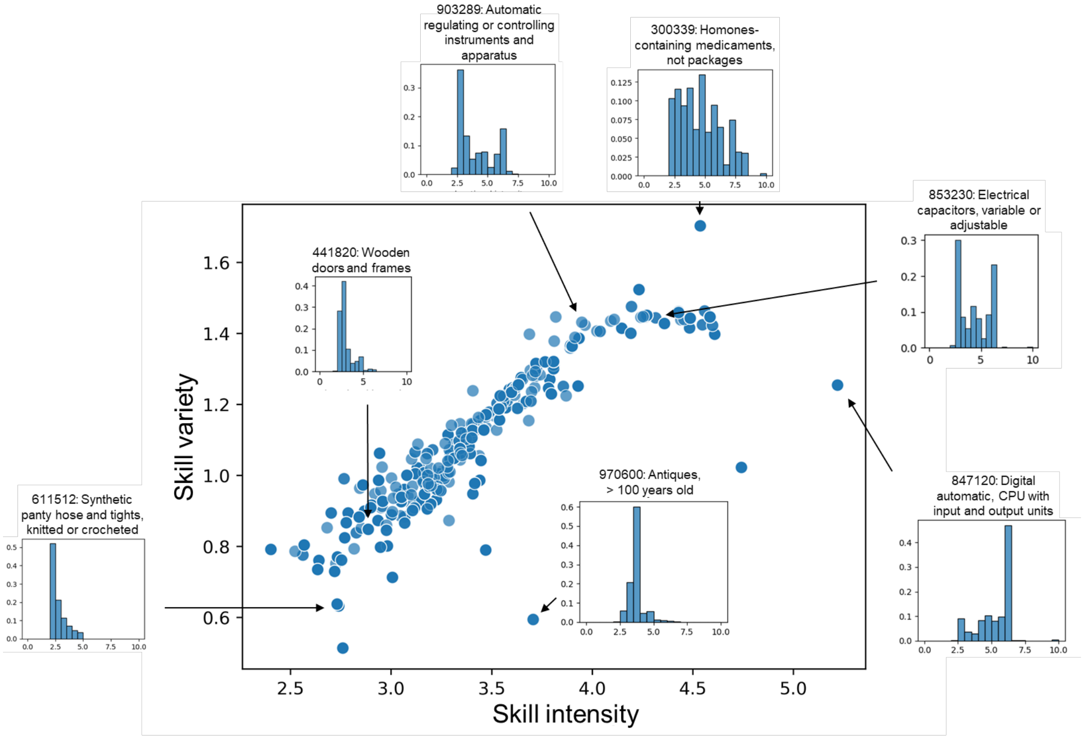


Figure 4: **Product skill intensity and skill variety.** Insets show for selected products the histogram over the skill intensity of all occupations required, weighted by the number of workers in that occupation.

This part of our work also relates to Kremer (1993)'s O-ring theory of development, which equates higher skill levels of workers with the ability to avoid mistakes during the production process. In the O-ring theory, the complementarity of workers and their tasks that result in a single product can turn small mistakes into large problems if not fixed in time. Kremer (1993) finds that complicated products that can be broken down into small parts are optimally allocated to a combination of low- and high-skilled workers, with high-skilled workers being allocated to later stages of production that integrate the components into full products. This interpretation would imply that more skill-intense products in our work can be broken down further than low skill-intense products, since both low- and high-skilled workers are required to make more skill-intense products. The data processing machinery and semiconductor industry may be different because it is intrinsically harder to break down into small and simpler components or because it is more vertically and geographically specialized than other industries.

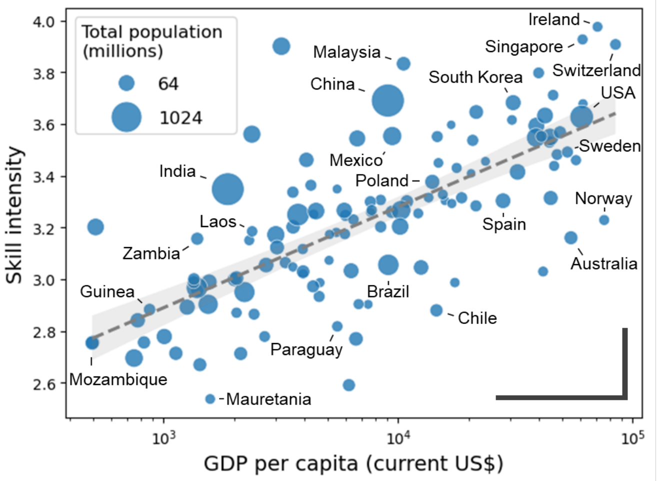
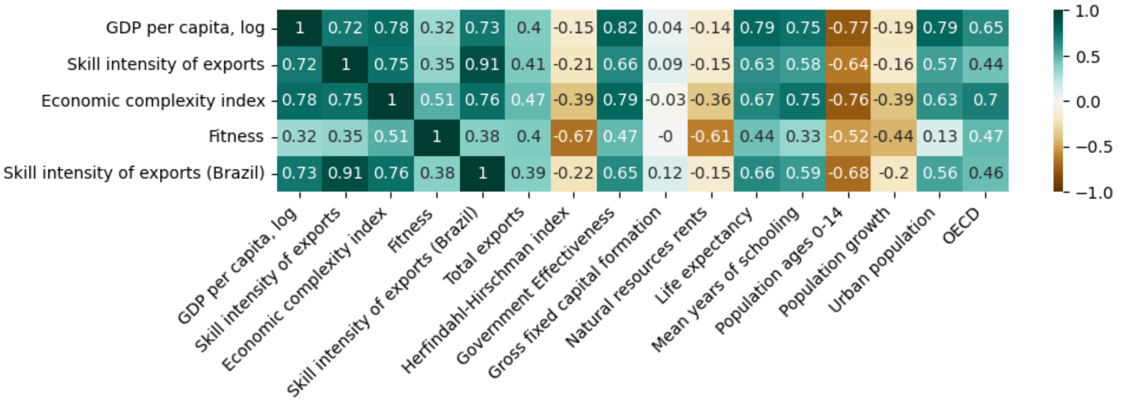


Figure 5: **Country skill intensity vs GDP per capita.** Data is for the 2015–2019 period. The size of each country corresponds to their population. The gray dashed line is the linear regression of country skill intensity on logged GDP per capita. The bottom right black bars indicate the size of 1 standard deviation.

Country-level insights

Our metric of country skill intensity correlates with GDP per capita, as shown in Fig. 5. Middle-income countries with a large manufacturing base, such as China and Malaysia, score relatively high for their level of income, whereas countries with strong resource-based export profiles, such as Norway and Australia, score relatively low compared to GDP per capita peers.

Fig. 6 shows the correlation between various country-level metrics. We find that country skill intensity correlates highest with ECI (0.75) and logged GDP per capita (0.72) and moderately with mean years of schooling (0.58), life expectancy (0.63), and urban population (0.57). Both country skill intensity and ECI correlate slightly negatively with growth, which is expected as countries with higher levels of country skill intensity and ECI tend to have higher GDP per capita levels, which often means they grow slower. In the next section, however, we find positive regression coefficients for both metrics when conditioning on initial levels of GDP per capita. A full correlation table with all variables can be found in Supplementary Materials Section I.



	GDP per capita, log	Skill intensity of exports	Economic complexity index	Fitness	Skill intensity of exports (Brazil)	Total exports	Herfindahl-Hirschman index	Government Effectiveness	Gross fixed capital formation	Natural resources rents	Life expectancy	Mean years of schooling	Population ages 0-14	Population growth	Urban population	OECD
GDP per capita, log	1	0.72	0.78	0.32	0.73	0.4	-0.15	0.82	0.04	-0.14	0.79	0.75	-0.77	-0.19	0.79	0.65
Skill intensity of exports	0.72	1	0.75	0.35	0.91	0.41	-0.21	0.66	0.09	-0.15	0.63	0.58	-0.64	-0.16	0.57	0.44
Economic complexity index	0.78	0.75	1	0.51	0.76	0.47	-0.39	0.79	-0.03	-0.36	0.67	0.75	-0.76	-0.39	0.63	0.7
Fitness	0.32	0.35	0.51	1	0.38	0.4	-0.67	0.47	-0	-0.61	0.44	0.33	-0.52	-0.44	0.13	0.47
Skill intensity of exports (Brazil)	0.73	0.91	0.76	0.38	1	0.39	-0.22	0.65	0.12	-0.15	0.66	0.59	-0.68	-0.2	0.56	0.46

Figure 6: **Pearson correlation coefficient between selected variables.**

Growth

While country skill intensity is correlated with GDP per capita, the variation in country skill intensity for a given GDP per capita level correlates positively with GDP per capita growth. Countries whose skill intensity is greater than their GDP per capita peers experience faster GDP per capita growth for the five years ahead (see Table 1). We use a pooled OLS that includes the current level of GDP per capita (GDPpc), logged, the Herfindahl-Hirschman index (HHI), which is a measure of export diversity, as well as our measure of country-level skill intensity (SkillInt):

$$g_c^{t \to t+5} = \alpha^{t-5,t} + \beta_1 \overline{\text{SkillInt}_c^{t-5,t}} + \beta_2 \log\left(\overline{\text{GDPpc}_c^{t-5,t}}\right) + \beta_3 \overline{\text{HHI}_c^{t-5,t}} + \epsilon_c^t, \tag{13}$$

where $g_c^{t \to t+t^*}$ is the annualized t^*-year GDP per capita growth starting from year t, $\overline{\text{x}_c^{t_1,t_2}}$ is the average value of x for country c between year t_1 and t_2, and α^{t_1,t_2} is the time fixed effect for the period from t_1 to t_2.

Besides the simple specification of Eq. (13), we also include a second model – our *full* specification – that additionally includes annual population growth, total natural resources rents as fraction of GDP, the amount of urbanization, gross fixed capital formation as fraction of GDP, and the fraction of the population that is below the age of 14, all from the World Bank Development Indicators (The World Bank, 2023), as well as government effectiveness from the World Bank Governance Indicators (The World Bank, 2024). We find that our metric is positive and robust for the different specifications. We include time fixed effects but do not have enough longitudinal depth for country fixed effects. The full expanded table can be found in Supplementary Materials Section J.1.

We compare our metric of country skill intensity with *mean years of schooling* as reported by UNDP (2022), a classical way to measure a country's skill intensity. Our proposed metric of country skill intensity and mean years of schooling perform similarly in terms of R-squared for the full specification. The 0.74 coefficient in the simple specification – model (1) in Table 1 – means that a one standard deviation change in the country skill intensity corresponds to 0.74%-point additional annualized growth for the next 5 years (see the black bars on the bottom right of Fig. 5 to see what one standard deviation looks like). Mean years of schooling performs better than country skill intensity in the simple specification but loses some of its explanatory power to other variables in the full specification.

We also show how our measure compares with ECI and Fitness, two other measures of know-how that have been used in the literature as predictors of GDP per capita growth. The Economic complexity index (ECI) was developed by Hidalgo and Hausmann (2009) and has been shown to be a significant predictor of GDP per capita. Finally, *Fitness* is an alternative measure of a country's economic complexity and was developed by Tacchella et al. (2012) and is also used to make growth predictions.

	Five-year future growth, annualized				
	(1)	(2)	(3)	(4)	(5)
GDP per capita, current USD, log	-1.41^{***}	-3.02^{***}	-2.81^{***}	-2.89^{***}	-2.82^{***}
	(0.22)	(0.48)	(0.48)	(0.57)	(0.49)
Country skill Intensity	0.74^{***}	0.51^{***}			
	(0.21)	(0.17)			
Mean years of schooling			0.54^{**}		
			(0.23)		
ECI				0.14	
				(0.31)	
Fitness					-0.05
					(0.21)
HHI	-0.41^{**}	0.11	0.06	0.08	0.04
	(0.18)	(0.25)	(0.25)	(0.27)	(0.26)
Fixed effects	Time	Time	Time	Time	Time
Full specification	No	Yes	Yes	Yes	Yes
Observations	444	444	444	444	444
R^2	0.15	0.32	0.32	0.31	0.31
Adjusted R^2	0.14	0.30	0.30	0.29	0.29
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table 1: **GDP per capita growth regression.** Panel Regression Models of five-year growth between 1995 and 2019, explained by country skill intensity (SkillInt). HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

In the Supplementary Materials, we include additional specifications, including for ten-year growth (Section J.2) and 20-year growth (Section J.3). The results are qualitatively similar, except that mean years of schooling has a slightly higher R-squared in the full specification for ten-year growth than our measure of country skill intensity. Mean years of schooling is the best predictor for twenty-year growth, followed by country skill intensity. In the Supplementary Materials, we also include *output multiplier* as an explanatory variable, which is a metric developed by McNerney et al. (2022) that performs well in growth regressions but is only defined for a small set of countries.

In Table S10 in Supplementary Materials Section J.5, we compare country skill intensity with mean years of schooling directly for the simple 5-, 10-, and 20-year growth regressions. When including country skill intensity together with mean years of schooling, both remain highly significant, indicating that the two measures are complementary.

Product skill intensity and country-level diversification

In this section, we explain how product skill intensity relates to path dependence in countries' export composition. Specifically, we look at how well the *skill distance* between a product's skill intensity and a country's mean years of schooling can explain variation in growth in the extensive margin: products that a country is newly competitive in.

In the Materials and methods section, we define the skill distance d^s_{cp} between product p and country c as the difference between the normalized mean years of schooling of country c and the normalized product skill intensity of product p. The skill abs distance $d^{s,\text{abs}}_{cp}$ is the absolute value of skill distance. We compare our approach with density, an alternative measure of distance between a product and a country. See the Materials and methods section for more details. We fit the following probit model to all product appearances J_{cpt} in our data:

$$P(J_{cpt} = 1) = \Phi\left(\beta_s d^s_{cp} + \beta_p d^p_{cp} + \beta^{\text{abs}}_s d^{s,\text{abs}}_{cp} + \gamma_p + \eta_c\right), \qquad (14)$$

where d_{cp}^{p} is the density of country c around product p, and γ_p and η_c are product and country fixed effects, respectively. Standard errors are clustered by country. Note that, in this specification, the product and country fixed effects absorb the product skill intensity and time-invariant part of the mean years of schooling of skill distance. The coefficient for skill distance (β_s) will thus note the propensity of countries to diversify faster in periods when their mean years of schooling is low. The results are shown in Table 2. Models (1)–(7) include the three variables of interest in different combinations.

	Dependent Variable: Appearance								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Skill distance	0.972***			1.07***	0.972***		1.07***	0.972***	
	(0.051)			(0.092)	(0.052)		(0.092)	(0.053)	
Density		0.556***		0.593***		0.552***	0.588***		0.564***
		(0.047)		(0.036)		(0.049)	(0.036)		(0.049)
Skill abs distance			-0.045***		-0.046***	-0.028***	-0.028***		
			(0.010)		(0.010)	(0.010)	(0.009)		
Skill dist. × yrs school								0.0465***	
								(0.0114)	
Density × yrs school									-0.1391***
									(0.0379)
Fixed effects									
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	8,330,062	8,515,152	8,330,062	8,330,062	8,330,062	8,330,062	8,330,062	8,330,062	8,330,062
Squared Correlation	0.0042	0.0038	0.0032	0.0052	0.0042	0.0038	0.0052	0.0041	0.0040
Pseudo R^2	0.0752	0.0772	0.0616	0.0940	0.0760	0.0783	0.0943	0.0759	0.0799

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: **Probit regression of product appearances.** Clustered standard errors by country.

We find that the coefficients of all three variables are significant and have the expected sign in all models. The coefficient of skill distance is positive, indicating that countries tend to diversify into more products in periods when their mean years of schooling is low. Similarly, the sign of density is positive, which shows that new products are 'nearby' a country's existing export basket in the product space. The negative coefficient for skill abs distance indicates that the skill intensity of products that appear has a relatively small skill distance to a country's level of schooling. Thus, the results for both density and skill abs distance indicate a tendency for products to appear when they are similar to the current export basket.

We find that density performs better than skill distance in terms of explained variance, which in turn outperforms skill abs distance. When including all three measures, they remain significant and are complementary. Together, however, they only explain less than 10% of the variance in product appearances, including the fixed effects.

In Models (8) and (9) in Table 2, we look at the interplay of a country's education level and diversification drivers. The results of Model (9) confirm the results of Felipe et al. (2024): years of schooling has a moderating effect on density. This indicates that density is less important for countries with more years of schooling. Model (8) shows that, conversely, years of schooling *increases* the importance of skill distance, although the effect is smaller. This latter result contrasts the result of Felipe et al. (2024), who found no such effect. Our results indicate that countries with higher education levels tend to diversify more often into products that are further away in terms of skill intensity and less constrained by density.

Discussion and conclusions

In this paper, we introduced *product skill intensity*, a new way to quantify product-level know-how. Our measure yields intuitive results, with computer components and medicaments scoring highly, while agricultural products and textiles receive lower scores. We find that products with similar skill intensity are often exported together. Products are grouped together in the product space network based on their product skill intensity, but not in a core-periphery manner.

We find that there is a strong linear relationship between a product's skill intensity and its *skill variety*, which is the extent to which a product requires diversity in the skill intensity of occupations in its production. We find that products with low product skill intensity predominantly require occupations with lower educational attainment, but high skill intense products require a diversity of workers of all skill-intensity levels. While increasing skill intensity might require a focus on skill shortages (see, e.g., Teixeira and Queirós, 2016; Zhu and Li, 2017; Diodato et al., 2022; Antonietti and Burlina, 2023; Schetter et al., 2024), the complementarity of occupations of different skill-intensity levels for high skill intense products points to the importance of cultivating diverse 'skill ecosystems' as countries develop (Neffke, 2019). Skill variety is also related to the concept of social capital, as the need for effective cooperation increases with higher levels of skill variety (Han et al., 2014).

At the country level, our measure of *country skill intensity* correlates with GDP per capita and is predictive of future GDP per capita growth. Our measure augments rather than confounds *mean years of schooling*, a traditional measure of human capital. This indicates that country skill intensity measures something complementary to educational attainment, namely the ability to transform learning and new skills into exported products – not unlike a 'learning society' envisaged by Stiglitz and Greenwald (2014). This is connected to earlier literature on the complementarity of human capital and entrepreneurship (Noseleit, 2013; Iyigun and Owen, 1999) and institutional quality (Costinot, 2009; Teixeira and Queirós, 2016), and the possible presence of human capital thresholds that countries need to clear before they are able to reap the benefits from export upgrading (Nouira and Saafi, 2022; Sheridan, 2014).

Finally, we quantified the *skill distance* between products and countries, and we found that countries tend to diversify into products that are relatively skill intense compared to their schooling level. An absolute measure of skill distance shows that countries are less likely to diversify into products with very different product skill intensity compared to a country's schooling level. While skill distance is outperformed by density (Hidalgo et al., 2007), it is complementary and highlights the direction of change. This relates to work by McNerney et al. (2023), who point out that density- and complexity-related measures both describe structural change, but they work at different timescales. Similar to skill distance, the longer timescale of complexity metrics also points in the direction of exporting more complex products over time (McNerney et al., 2023). Furthermore, our results show that countries with higher education levels are less constrained by density, which is consistent with Felipe et al. (2024). In contrast to their results, however, we find an increasing importance of skill distance in explaining variation in export diversification paths for countries with higher education levels. Our results indicate that countries with higher education levels tend to diversify into products that are more skill intense and further away from their current export basket in terms of relatedness. This is consistent with but goes beyond the results by Schetter et al. (2024), who find that higher-educated countries tend to diversify into products that require more skilled occupations.

Our work contributes to the literature in three distinct ways. First, our product-level measures of skill intensity and skill variety can be additional tools for researchers to explore a variety of questions in trade and development studies and other fields. We make this data freely available online.

Second, our work highlights a new dimension of polarization of the product space. While previous literature on the product space and economic complexity has identified the core-periphery structure of the product space, we additionally observe that one side of the product space tends to be low-skill and the other side high-skill. This could have implications for studying the middle-income trap. Diversifying into the densely connected core may not be enough if a country is still in the low skill intense region of the product space. Perhaps it is a first step, with further diversification required towards the products of higher sophistication in later stages of development. This echoes the seminal contribution of Imbs and Wacziarg (2003), who find that countries first diversify their export basket but later specialize again when reaching high-income status.

Third, our measures of country skill intensity and skill distance shed light on how countries have been able to capitalize on their labor force and secure per capita

GDP growth. These measures aim to capture how education translates into one of the most important applications for a country's growth and development: the ability to export more sophisticated products. It overcomes some of the weaknesses of measures of educational attainment, which can obfuscate educational quality differences or, more subtly, hide over-education (Mehta et al., 2011), as well as of other product-based measures, such as ECI and Fitness, that are indirect and only defined relative to other countries.

There are many avenues for future work. First, our definition of product skill intensity uses US data as a proxy for the competitive exports of all countries, which has drawbacks. Even though we show that it highly correlates with a measure based on Brazilian data, there will be differences between all 125 countries in our sample that may be worth exploring (Brambilla et al., 2012; Lo Bello et al., 2019; Caunedo et al., 2023). For example, Kruse et al. (2023) show for 20 sectors in 59 countries that countries initially shift to more complex industries but later specialize *within* an industry. While our data is more disaggregated, our measure would fail to pick up on very detailed product differentiation. Second, we made the abstraction that a product's skill intensity is fixed over time. We have seen an acceleration of automation in recent decades that might change some products more than others (Acemoglu and Restrepo, 2019). More research into automation is needed to understand its impact on skilled manufacturing and development outcomes (Balland et al., 2022). Third, our measures of product and country skill intensity, skill variety and skill distance are one-dimensional metrics, but skills are inherently heterogeneous, multi-dimensional, and not easily substitutable (Acemoglu and Autor, 2011; Neffke, 2019; Johnson, 2020; Schetter et al., 2024). For example, nursing skills are very different from construction skills. Indeed, our measure of skill variety highlights this diversity. However, we have kept our methods simple and easy to interpret while telling a nuanced yet powerful story of development through learning and applied know-how. Future work can try to understand in what cases a more involved multi-dimensional measure would be better, or it can explore further the connection between product skill intensity and skill variety, which both may add to the overall 'complexity' of a product. Fourth, our measure of product skill intensity builds on data on workers' formal education, but many routes to acquiring skills exist that do not involve formal education, such as on-the-job training and experience more generally. The extent to which these are important may vary depending on the occupation or industry involved. Furthermore, our export-based measures currently ignore services exports, which are sizable and becoming more important.

In this work, we have introduced new ways of looking at the know-how embedded in products and country-level exports. These methods can help understand the heterogeneity and path-dependence of development, and researchers and policymakers can use the skill intensity measures we have introduced to address new research and policy-relevant questions.

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Supplementary Materials

Contents

A Occupational skill intensity

In the Materials and methods section in the main text, we calculate product skill intensity by taking the average educational attainment of the occupations that are required in industries that produce those products (see Materials and methods section Eqs. (1)-(3)). Here, in Fig. S1, we show a histogram of the average educational attainment of workers per occupation. All occupations have a skill intensity between 1.9 and 8.0, and 90% of occupations between 2.3 and 7.1. Judges and some medical specializations have the highest skill intensity, some construction and agricultural trades the lowest.

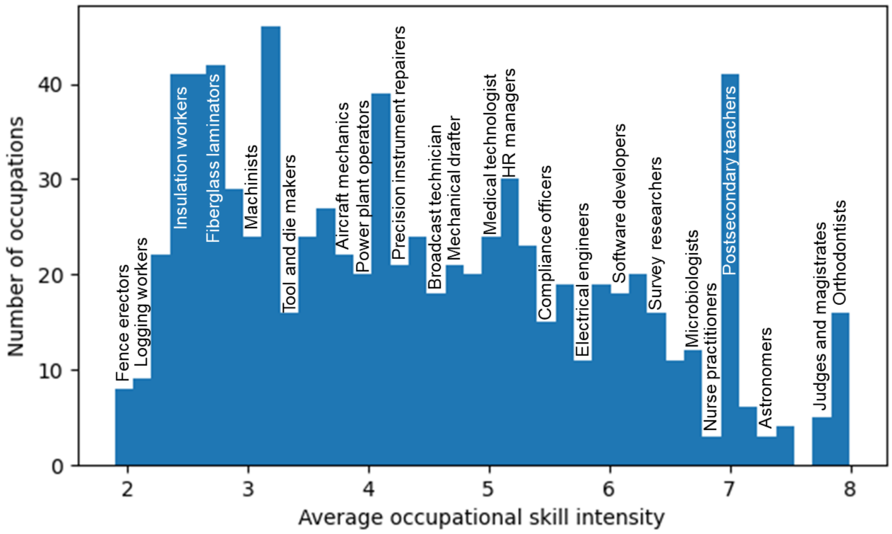

Figure S1: **Histogram of occupations by their skill intensity.** Selected values of occupational skill intensity are labeled with example occupations.

B Wage vs skill intensity per schooling level

Skill intensity scores of workers are correlated with their average wages. In Table S1, we use data from BLS[8] and find a monotonous increase in earnings per skill intensity score.

Education level	Skill intensity	Median weekly earnings (2022-USD)
PhD	8	2,083
MSc	7	1,661
BSc	6	1,432
Associate's degree	5	1,005
Some college	4	935
Postsecondary nondegree	3	
High school	2	853
Less than high school	1	682

Table S1: *Earnings per skill intensity level.* Data on weekly median earnings from BLS

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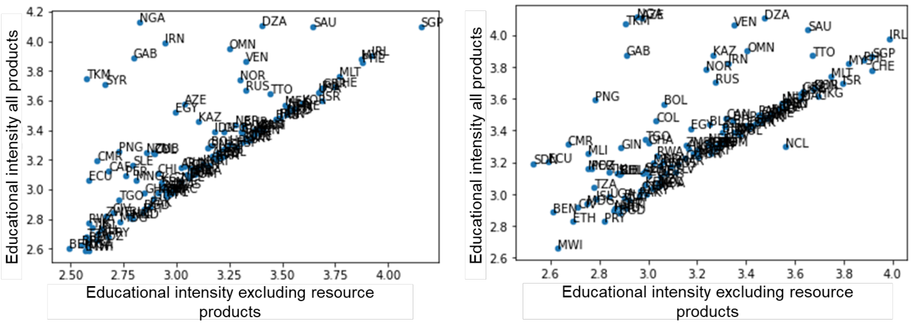
[8] https://www.bls.gov/careeroutlook/2023/data-on-display/education-pays.htm

C Resource-based products

As mentioned in the Materials and methods section, we exclude from our analysis all resource-based products. In Fig. S2, we show a scatter plot of country skill intensity, with on the x-axis our measure of country skill intensity and on the y-axis the average skill intensity of all exported products, including resource-based products. Most countries are located around the identity line, indicating both metrics are very similar, but some countries have different scores. Some oil and gas products are very skill intensive and non-diversified oil-exporting countries, such as Nigeria and Azerbaijan, thus have a much lower skill intensity after excluding resource-based products. More diversified fossil fuel exporters, such as Norway and Ghana, also show a significant divergence. New Caledonia is the only country that scores markedly higher on country skill intensity after excluding resource products. This is because a large part of its exports are nickel ores, which are much less skill intensive than fossil fuels as well as the rest of New Caledonia's exports.



(a) 1995-1999

(b) 2015-2019

Figure S2: **Country skill intensity excluding and including resource products.** The two plots show data for different time periods: a) 1995–1999 and b) 2015–2019.

D Product categories

Table S2 lists the product categories used in the main text and their corresponding HS codes.

HS starting codes	Product category
01–05	Animals & animal products
06–15	Vegetable products
16–24	Foodstuff
25–27	Mineral products
28–38	Chemicals & allied products
39–40	Plastics & rubbers
41–43	Leather & hides
44–49	Wood & wood products
50–63	Textiles
64–67	Footwear & headgear
68–71	Stone & glass
72–83	Metals
84–85	Machinery & electrical products
86–89	Transportation products
90–97	Miscellaneous products

Table S2: **Product categories and their corresponding HS two-digit starting codes.**

E Skill intensity vs product complexity index (PCI)

Table S3 shows that the product complexity index (PCI) by Hidalgo et al. (2007) correlates with our measure of skill intensity with a Pearson correlation coefficient of about 0.5, suggesting a moderate correlation. Table S3 additionally shows the correlation between the skill intensity measured for the US and Brazil, as well as PCI measured for two different periods in our dataset (1998–2002 and 2015–2019).

We find a high correlation of 0.8 between the two skill intensity measures. We also find a 0.8 correlation coefficient between PCI measured around 2000 and PCI measured in the late 2010s.

In Fig. S3, we plot the 2017 PCI against product skill intensity and color each product by their product category. We find that skill intensity groups products more by their categories, whereas products in the same category can have very divergent PCI values. For example, *Gum Arabic* and *Mosses and Lichens* have similar skill intensity but are found at the opposite spectrum of PCI. On the other hand, skill intensity has a lot of variety in machinery and electrical appliances.

	Skill intensity	Skill intensity Br	PCI ('98–'02)	PCI ('15–'19)
Skill intensity	1.0	0.8	0.5	0.5
Skill intensity Br	0.8	1.0	0.5	0.5
PCI ('98-'02)	0.5	0.5	1.0	0.8
PCI ('15-'19)	0.5	0.5	0.8	1.0

Table S3: **Correlation between product skill intensity and PCI.** Pearson correlation coefficients between product skill intensity (based on US or Brazilian (Br) data) and product complexity index (PCI, for the 1998–2002 and 2015–2019 periods).

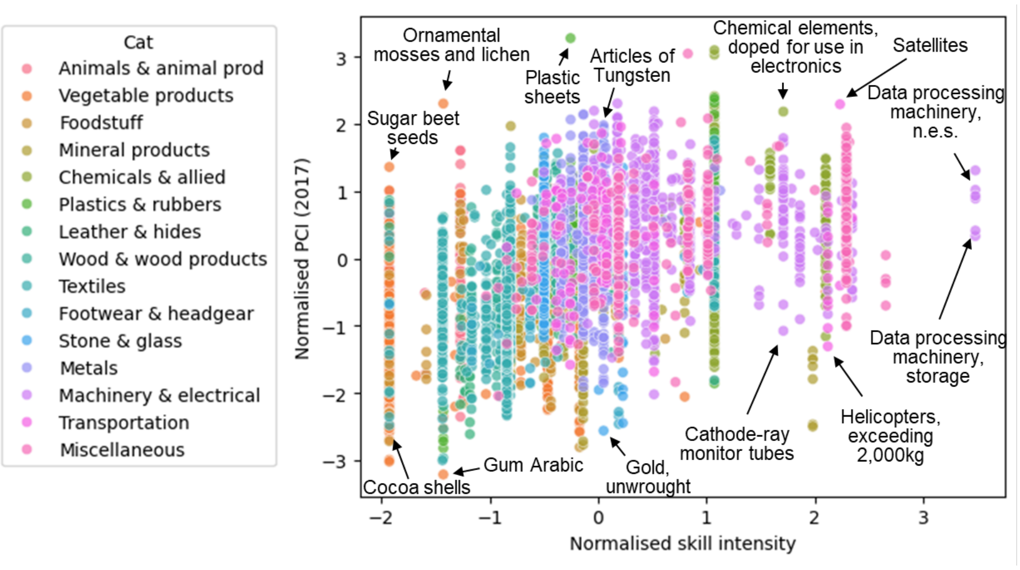
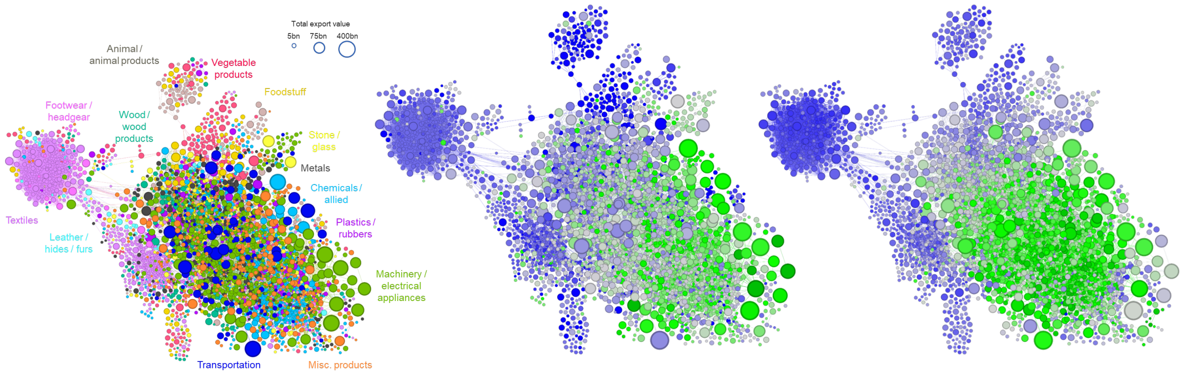


Figure S3: **PCI vs skill intensity.** Scatter plot of PCI calculated using the 2017 export data, and skill intensity using US data. Each product is colored by their product category. Selected products are labeled.

Fig. S4c shows the product space with products colored by PCI. For comparison, Fig. S4a and S4b reproduce Fig. 3 and show the product space with products colored by product category and skill intensity, respectively.



(a) Product category (b) Skill intensity (c) Product complexity (PCI)

Figure S4: **The product space.** Products (nodes) are connected if they are often co-exported. The edge width indicates the strength of the connection, and the node size reflects the total global export value of that product. The node color reflects in a) the product category; b) skill intensity; and c) product complexity (PCI). Only the maximum spanning tree and all other links larger than three standard deviations above the mean (0.56) are shown. The layout was created using a force-pull algorithm, as implemented in Gephi, modified to minimize node overlap and retouched by hand.

F Product space assortativity

In this section, we calculate the skill intensity assortativity on the product space for different values of the threshold r, which we set in the main text to 0.56. This threshold governs at what level of proximity – or co-export probability – ϕ_{ij} between products i and j we add an edge in the network. Note that we always include the maximum spanning tree and exclude self-loops ϕ_{ii}. In Fig. S5, we find positive values of assortativity for all threshold values, with the maximum assortativity reached for $r = \mu + 4\sigma = 0.56$.

We also estimate the correlation between product skill intensity and three other network metrics: node degree, coreness and centrality. All these metrics quantify in some way the connectedness of a product in the network. The *degree* of a node is the number of other nodes it is connected to. High-degree products are 'hub'-products; they are proximate to many other products. For most values of r, we find a small negative correlation between the degree and skill intensity of a product.

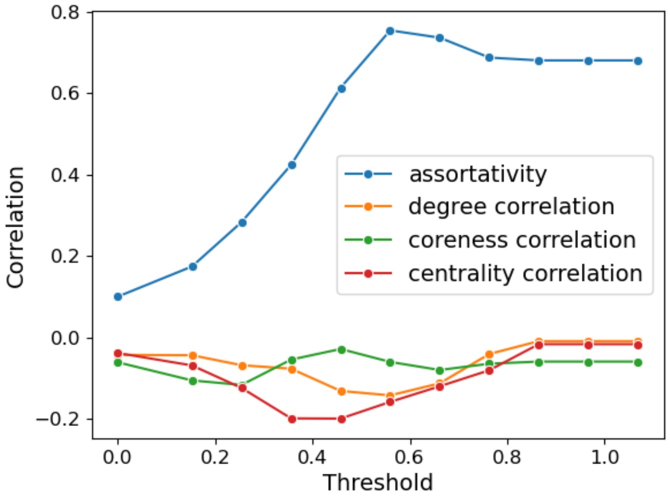


Figure S5: **Skill intensity assortativity, coreness, centrality, and degree correlation in the product space for different threshold values.** Correlations are Pearson correlation coefficients of skill intensity with node strength, core number, and eigenvector centrality.

We calculate the *coreness* of a node by taking the core number by Batagelj and Zaversnik (2003) as implemented in the python package NetworkX. Let the k-core be the subgraph of G that contains nodes of degree k or more in the subgraph. This is not merely a collection of all nodes with degree k or more *in the full graph* G, but with degree k or more in the *subgraph*, thus after having removed lower-degree nodes. The core number of a node is the largest value of k for which the node is in the k-core. The core number is slightly negatively correlated with skill intensity for all values of r.

Finally, the eigenvector *centrality* is a proxy for the importance of a node in the entire network structure. We also find a low negative correlation between eigenvector centrality and skill intensity.

G Robustness with Brazil data

In the main text, we use US data to calculate the skill intensity of products, which we use as a proxy for the global technological frontier of exported goods. However, there will be differences in the types and number of workers that are employed to manufacture the same product in different countries (e.g., Brambilla et al., 2012).

Nonetheless, we think our approach is an acceptable proxy, because exports compete in a global market, and some convergence towards the technological frontier for exported products can thus be expected. Furthermore, Keesing (1971) showed that, for his measure, a US proxy of skill intensity works well and is very similar to using any of nine other, mostly industrialized countries.

As a robustness check, we create an alternative product skill intensity metric using data on manufacturing labor in Brazil, a middle-income country. We use data from RAIS (Relação Anual de Informações Sociais), which is an annual survey of the formal labor market in Brazil (Brasil Ministry of Labor and Employment, 2022). RAIS contains the occupation and industry of workers, as well as their educational attainment. We also use a crosswalk from RAIS's industry classification to the HS classification of products.

Table S4 shows the skill intensity scores for educational attainment levels in Brazil, which we chose to keep them in line with the values we used for the US data in Fig. 1.

US category	US skill intensity	RAIS category (Portuguese)	RAIS category (translation)	Brazil skill intensity
Less than high school diploma	1	Analfabeto	Illiterate	0
		Até o 5ª ano Incompleto do Ensino Fundamental	Elementary School incomplete (less than 5th year)	0.3
		5ª ano Completo do Ensino Fundamental	5th complete year of Elementary School	0.5
		Do 6ª ao 9ª ano Incompleto do Ensino Fundamental	Elementary School incomplete (6th - 9th year)	0.8
		Ensino Fundamental Completo	Complete Elementary School	1
		Ensino Médio Incompleto	Incomplete High School	1.5
High school diploma or equivalent	2	Ensino Médio Completo	Complete High School	2
Postsecondary nondegree award	3	Educação Superior Incompleta	Incomplete Higher Education	4
Some college, no degree	4			
Associate's degree	5	Educação Superior Completa	Complete Higher Education	5
Bachelor's degree	6			
Master's degree	7	Mestrado Completo	Master's Degree	7
Doctoral or professional degree	8	Doutorado Completo	Doctorate	8

Table S4: **Skill intensity per schooling level** e_s.

In Fig. S6, we plot both skill intensity metrics, with products colored by their product category. The correlation between the Brazil and US product skill intensity scores is 0.8. While the exact values of skill intensity differ, the correlation is strong.

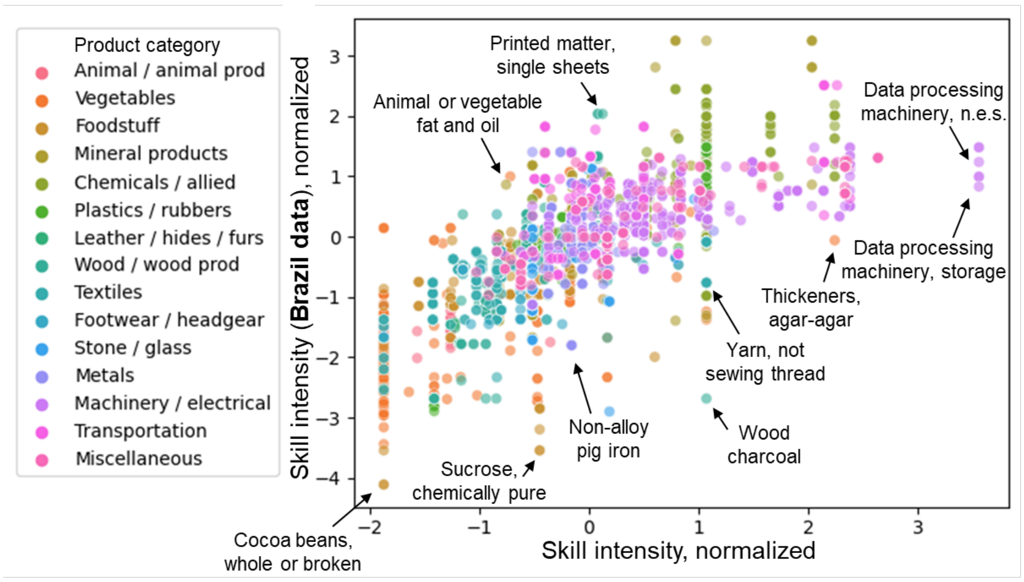
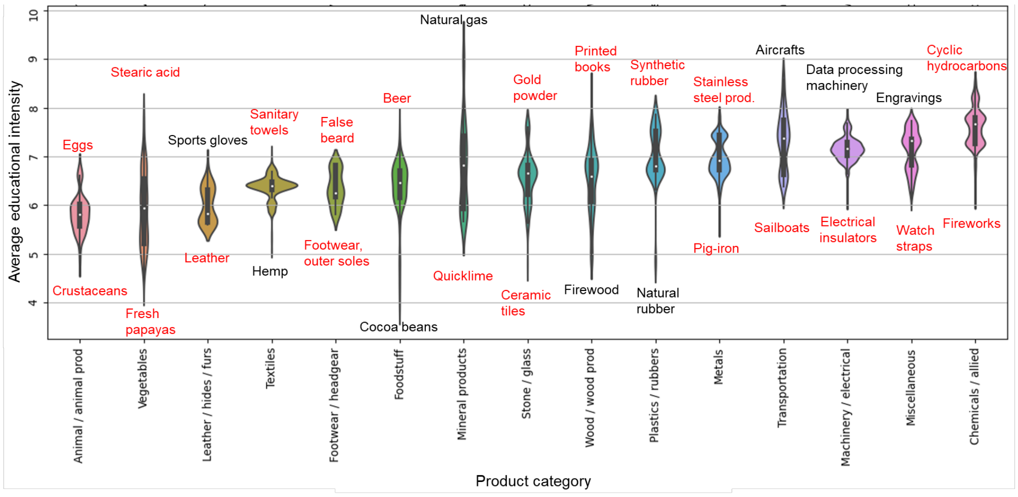


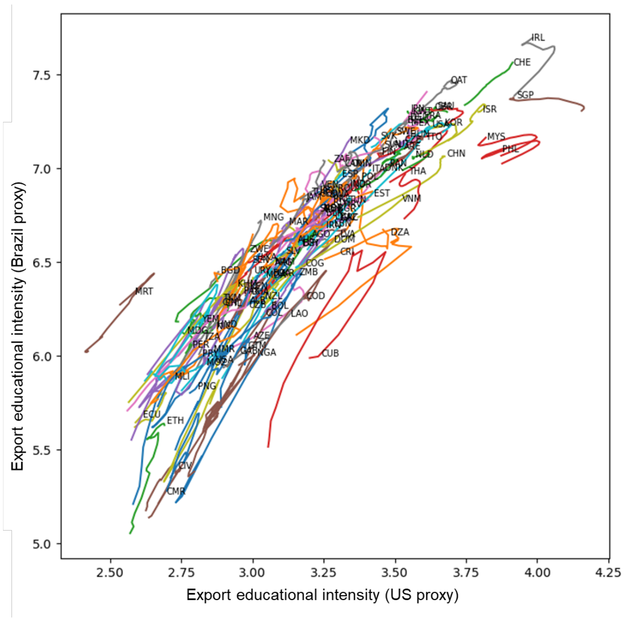
Figure S6: **Product skill intensity vs Brazil product skill intensity.** Skill intensity in the US (x-axis) and Brazil (y-axis) for 6-digit products colored by their 1-digit product categories. Skill intensity values are normalized to zero-mean, unit-standard deviation variables. Selected products are labeled.

Fig. S7a recreates Fig. 2 for Brazil. The ordering of product categories is very similar but slightly different: In Brazil, as opposed to the US, Vegetable products are more skill intense than Leather & hides, Textiles more than Footwear & headgear, Mineral products more than Stone & glass and Wood & wood products, and Transportation more than Machinery & electrical. Within categories, products also have a different ranking. We highlight the most and least skill intense products per category in red if they differ from the US.

In Fig. S7b, we show the change in country skill intensity over time. Country skill intensity has a Pearson correlation coefficient of 0.9 between the Brazil and US proxies. Most of the time, the change in both metrics is in the same direction (bottom-left to top-right movements and vice versa), although we also observe some small movements in the opposite direction (top-left to bottom-right and vice versa), which indicates an increase in one of the metrics, and a decrease in the other.



(a) Brazil product skill intensity between and within product categories. The most and least skill intense product per product category is labeled. Labels that are colored red indicate that the top or bottom product in the US proxy was not present in the top three products in Brazil.



(b) Country trajectories of country skill intensity using US (x-axis) and Brazil data (y-axis).

Figure S7: **Brazil vs US product skill intensity.**

In Fig. 4 in the main text, we find a linear relationship between skill intensity and skill variety. We find a similar linear relationship between skill variety and skill intensity using the Brazil metric in Fig. S8.

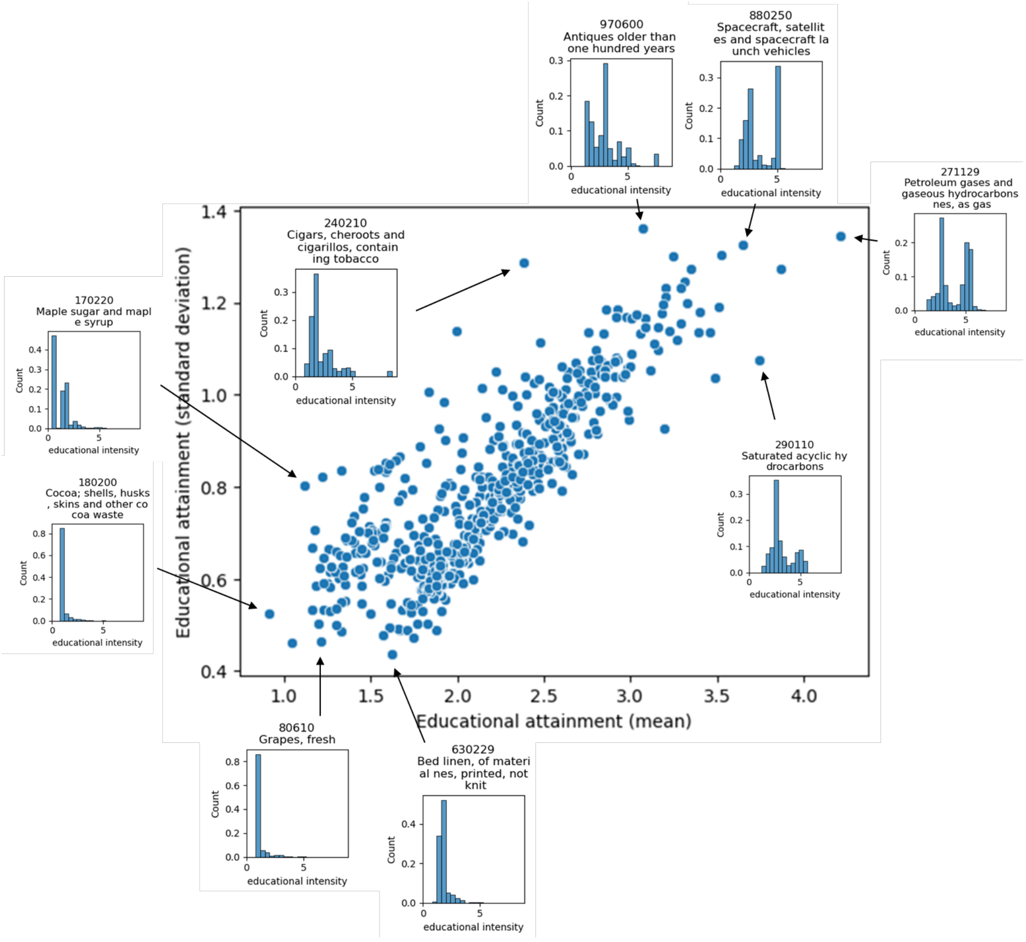


Figure S8: **Skill variety vs skill intensity of products, using Brazil product skill intensity.**

H Country data included

We include 125 countries in our main analysis. From the initial list of countries in our country data, we follow Albeaik et al. (2017) in excluding:

- Countries with a population of less than 1.25 million in 2008;
- Countries with exports of less than 1 billion in 2008;
- Chad (TCD), Iraq (IRQ), and Afghanistan (AFG);
- In addition to Albeaik et al. (2017), we further remove North Korea (PRK) and Hong Kong (HKG).

Table S5 lists all countries included in our study.

ALB
DZA
AGO
ARG
AUS
AUT
AZE
BGD
BLR
BEL
BIH
BWA
BRA
BGR
KHM
CMR
CAN
CHL
CHN
HKG
COL
COG
CRI
HRV
CUB
CZE
PRK
COD
DNK
DOM
ECU
EGY
SLV
EST
ETH
FIN
FRA
GAB
GEO
DEU
GHA
GRC
GTM
GIN
HND
HUN
IND
IDN
IRN
IRL
ISR
ITA
CIV
JAM
JPN
JOR
KAZ
KEN
KWT
LAO
LVA
LBN
LBY
LTU
MDG
MYS
MLI
MRT
MEX
MNG
MAR
MOZ
MMR
NAM
NLD
NZL
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NOR
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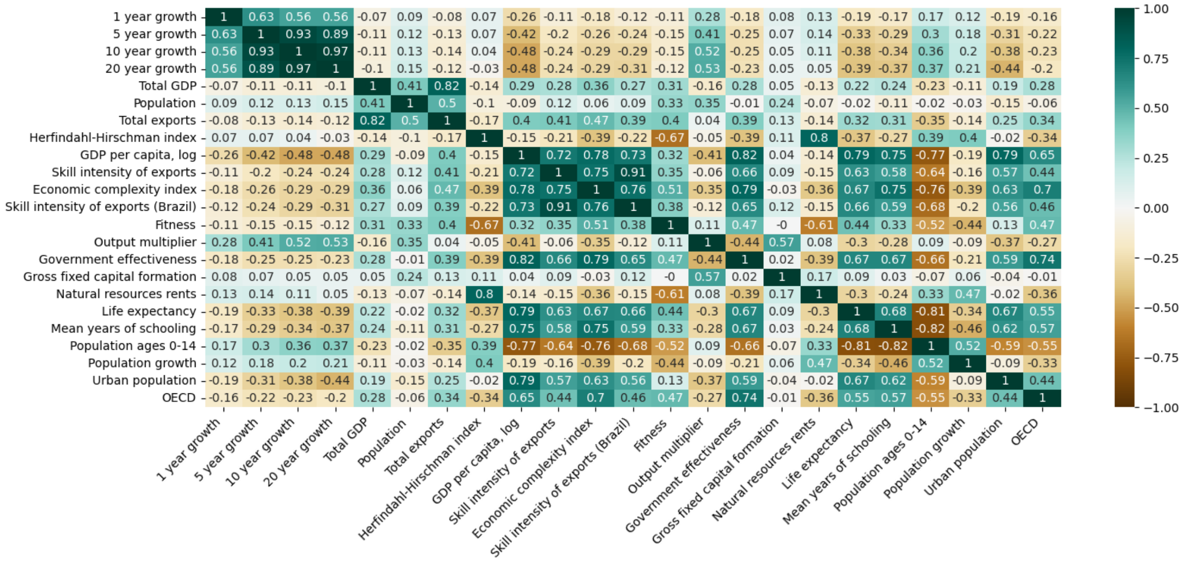
RUS
SAU
SEN
SRB
SGP
SVK
SVN
ZAF
ESP
LKA
SWE
CHE
SYR
THA
MKD
TTO
TUN
TUR
TKM
USA
UGA
UKR
ARE
GBR
TZA
URY
UZB
VEN
VNM
YEM
ZMB
ZWE

Table S5: **Countries included in this study.**

I Correlations at the country level

Fig. S9 shows the correlation matrix that includes all variables of our study. This is an extension of Fig. 6 in the main text.



	1 year growth	5 year growth	10 year growth	20 year growth	Total GDP	Population	Total exports	Herfindahl-Hirschman index	GDP per capita, log	Skill intensity of exports	Economic complexity index	Skill intensity of exports (Brazil)	Fitness	Output multiplier	Government effectiveness	Gross fixed capital formation	Natural resources rents	Life expectancy	Mean years of schooling	Population ages 0-14	Population growth	Urban population	OECD
1 year growth	1	0.63	0.56	0.56	-0.07	0.09	-0.08	0.07	-0.26	-0.11	-0.18	-0.12	-0.11	0.28	-0.18	0.08	0.13	-0.19	-0.17	0.17	0.12	-0.19	-0.16
5 year growth	0.63	1	0.93	0.89	-0.11	0.12	-0.13	0.07	-0.42	-0.2	-0.26	-0.24	-0.15	0.41	-0.25	0.07	0.14	-0.33	-0.29	0.3	0.18	-0.31	-0.22
10 year growth	0.56	0.93	1	0.97	-0.11	0.13	-0.14	0.04	-0.48	-0.24	-0.29	-0.29	-0.15	0.52	-0.25	0.05	0.11	-0.38	-0.34	0.36	0.2	-0.38	-0.23
20 year growth	0.56	0.89	0.97	1	-0.1	0.15	-0.12	-0.03	-0.48	-0.24	-0.29	-0.31	-0.12	0.53	-0.23	0.05	0.05	-0.39	-0.37	0.37	0.21	-0.44	-0.2
Total GDP	-0.07	-0.11	-0.11	-0.1	1	0.41	0.82	-0.14	0.29	0.28	0.36	0.27	0.31	-0.16	0.28	0.05	-0.13	0.22	0.24	-0.23	-0.11	0.19	0.28
Population	0.09	0.12	0.13	0.15	0.41	1	0.5	-0.1	-0.09	0.12	0.06	0.09	0.33	0.35	-0.01	0.24	-0.07	-0.02	-0.11	-0.02	-0.03	-0.15	-0.06
Total exports	-0.08	-0.13	-0.14	-0.12	0.82	0.5	1	-0.17	0.4	0.41	0.47	0.39	0.4	0.04	0.39	0.13	-0.14	0.32	0.31	-0.35	-0.14	0.25	0.34
Herfindahl-Hirschman index	0.07	0.07	0.04	-0.03	-0.14	-0.1	-0.17	1	-0.15	-0.21	-0.39	-0.22	-0.67	-0.05	-0.39	0.11	0.8	-0.37	-0.27	0.39	0.4	-0.02	-0.34
GDP per capita, log	-0.26	-0.42	-0.48	-0.48	0.29	-0.09	0.4	-0.15	1	0.72	0.78	0.73	0.32	-0.41	0.82	0.04	-0.14	0.79	0.75	-0.77	-0.19	0.79	0.65
Skill intensity of exports	-0.11	-0.2	-0.24	-0.24	0.28	0.12	0.41	-0.21	0.72	1	0.75	0.91	0.35	-0.06	0.66	0.09	-0.15	0.63	0.58	-0.64	-0.16	0.57	0.44
Economic complexity index	-0.18	-0.26	-0.29	-0.29	0.36	0.06	0.47	-0.39	0.78	0.75	1	0.76	0.51	-0.35	0.79	-0.03	-0.36	0.67	0.75	-0.76	-0.39	0.63	0.7
Skill intensity of exports (Brazil)	-0.12	-0.24	-0.29	-0.31	0.27	0.09	0.39	-0.22	0.73	0.91	0.76	1	0.38	-0.12	0.65	0.12	-0.15	0.66	0.59	-0.68	-0.2	0.56	0.46
Fitness	-0.11	-0.15	-0.15	-0.12	0.31	0.33	0.4	-0.67	0.32	0.35	0.51	0.38	1	0.11	0.47	-0	-0.61	0.44	0.33	-0.52	-0.44	0.13	0.47
Output multiplier	0.28	0.41	0.52	0.53	-0.16	0.35	0.04	-0.05	-0.41	-0.06	-0.35	-0.12	0.11	1	-0.44	0.57	0.08	-0.3	-0.28	0.09	-0.09	-0.37	-0.27
Government effectiveness	-0.18	-0.25	-0.25	-0.23	0.28	-0.01	0.39	-0.39	0.82	0.66	0.79	0.65	0.47	-0.44	1	0.02	-0.39	0.67	0.67	-0.66	-0.21	0.59	0.74
Gross fixed capital formation	0.08	0.07	0.05	0.05	0.05	0.24	0.13	0.11	0.04	0.09	-0.03	0.12	-0	0.57	0.02	1	0.17	0.09	0.03	-0.07	0.06	-0.04	-0.01
Natural resources rents	0.13	0.14	0.11	0.05	-0.13	-0.07	-0.14	0.8	-0.14	-0.15	-0.36	-0.15	-0.61	0.08	-0.39	0.17	1	-0.3	-0.24	0.33	0.47	-0.02	-0.36
Life expectancy	-0.19	-0.33	-0.38	-0.39	0.22	-0.02	0.32	-0.37	0.79	0.63	0.67	0.66	0.44	-0.3	0.67	0.09	-0.3	1	0.68	-0.81	-0.34	0.67	0.55
Mean years of schooling	-0.17	-0.29	-0.34	-0.37	0.24	-0.11	0.31	-0.27	0.75	0.58	0.75	0.59	0.33	-0.28	0.67	0.03	-0.24	0.68	1	-0.82	-0.46	0.62	0.57
Population ages 0-14	0.17	0.3	0.36	0.37	-0.23	-0.02	-0.35	0.39	-0.77	-0.64	-0.76	-0.68	-0.52	0.09	-0.66	-0.07	0.33	-0.81	-0.82	1	0.52	-0.59	-0.55
Population growth	0.12	0.18	0.2	0.21	-0.11	-0.03	-0.14	0.4	-0.19	-0.16	-0.39	-0.2	-0.44	-0.09	-0.21	0.06	0.47	-0.34	-0.46	0.52	1	-0.09	-0.33
Urban population	-0.19	-0.31	-0.38	-0.44	0.19	-0.15	0.25	-0.02	0.79	0.57	0.63	0.56	0.13	-0.37	0.59	-0.04	-0.02	0.67	0.62	-0.59	-0.09	1	0.44
OECD	-0.16	-0.22	-0.23	-0.2	0.28	-0.06	0.34	-0.34	0.65	0.44	0.7	0.46	0.47	-0.27	0.74	-0.01	-0.36	0.55	0.57	-0.55	-0.33	0.44	1

Figure S9: **Pearson correlation coefficient for all variables used in this study.**

J Growth regressions

J.1 5 year growth, extended

	Five-year future growth, annualized									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP per capita, current USD, log	-1.41^{***}	-3.02^{***}	-1.89^{***}	-2.81^{***}	-1.57^{***}	-2.89^{***}	-1.00^{***}	-2.82^{***}	-1.30^{***}	-2.14^{***}
	(0.22)	(0.48)	(0.24)	(0.48)	(0.37)	(0.57)	(0.18)	(0.49)	(0.20)	(0.56)
SkillInt	0.74^{***}	0.51^{***}								
	(0.21)	(0.17)								
Mean years of schooling			1.38^{***}	0.54^{**}						
			(0.22)	(0.23)						
ECI					0.85^{**}	0.14				
					(0.37)	(0.31)				
Fitness							0.39	−0.05		
							(0.25)	(0.21)		
Output multiplier									0.69^{**}	0.63^{**}
									(0.28)	(0.29)
HHI	-0.41^{**}	0.11	-0.33^{**}	0.06	−0.29	0.08	−0.26	0.04	0.18	0.13
	(0.18)	(0.25)	(0.15)	(0.25)	(0.20)	(0.27)	(0.22)	(0.26)	(0.14)	(0.29)
Pop., aged 0-14 (% of total pop.)		-1.09^{**}		-0.96^{**}		-1.21^{***}		-1.25^{***}		0.14
		(0.52)		(0.46)		(0.46)		(0.47)		(0.45)
Pop. growth (annual %)		−0.65		−0.51		−0.58		−0.60		-0.64^{**}
		(0.43)		(0.35)		(0.38)		(0.37)		(0.28)
Tot. nat. res. rents (% of GDP)		0.14		0.09		0.17		0.17		0.18
		(0.39)		(0.34)		(0.37)		(0.37)		(0.31)
Urban. pop. (% of total pop.)		0.22		0.13		0.22		0.21		0.12
		(0.21)		(0.22)		(0.22)		(0.23)		(0.28)
Gross fixed cap form (% of GDP)		0.30^{*}		0.33^{*}		0.33^{*}		0.32^{*}		0.16
		(0.16)		(0.18)		(0.18)		(0.17)		(0.29)
Government effectiveness		0.73^{***}		0.69^{***}		0.80^{***}		0.83^{***}		1.03^{***}
		(0.24)		(0.24)		(0.23)		(0.24)		(0.36)
Fixed effects	Time	Time	Time	Time	Time	Time	Time	Time	Time	Time
Full specification	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	444	444	444	444	444	444	444	444	108	108
R^2	0.15	0.32	0.23	0.32	0.14	0.31	0.12	0.31	0.55	0.64
Adjusted R^2	0.14	0.30	0.22	0.30	0.13	0.29	0.11	0.29	0.53	0.60

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table S6: **Growth regression (extended).** Panel Regression Models of five year growth between 1995 and 2019, explained by weighted average skill intensity of exports. HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

J.2 10 year growth

	Ten-year future growth, annualized									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP per capita, current USD, log	−1.44***	−2.66***	−1.89***	−2.40***	−1.54***	−2.56***	−1.06***	−2.46***	−1.25***	−1.89***
	(0.22)	(0.46)	(0.24)	(0.44)	(0.37)	(0.54)	(0.17)	(0.45)	(0.17)	(0.52)
SkillInt	0.64***	0.39**								
	(0.21)	(0.18)								
Mean years of schooling			1.30***	0.80***						
			(0.23)	(0.26)						
ECI					0.69*	0.13				
					(0.36)	(0.33)				
Fitness							0.23	−0.21		
							(0.26)	(0.22)		
Output multiplier									0.64***	0.57**
									(0.22)	(0.26)
HHI	−0.45**	−0.16	−0.37**	−0.19	−0.38*	−0.20	−0.38	−0.30	0.06	0.32
	(0.19)	(0.28)	(0.15)	(0.26)	(0.21)	(0.29)	(0.23)	(0.28)	(0.22)	(0.38)
Population growth (annual %)		−0.22		−0.03		−0.17		−0.19		−0.29
		(0.36)		(0.21)		(0.31)		(0.29)		(0.33)
Pop, aged 0-14 (% of total pop)		−1.08**		−0.77**		−1.16***		−1.26***		0.07
		(0.43)		(0.36)		(0.38)		(0.38)		(0.42)
Tot. nat. res. rents (% of GDP)		0.07		−0.05		0.10		0.08		−0.20
		(0.44)		(0.37)		(0.43)		(0.43)		(0.34)
Urban pop (% of total pop)		0.32		0.15		0.32		0.28		−0.11
		(0.23)		(0.23)		(0.22)		(0.23)		(0.23)
Gross fixed cap form (% of GDP)		0.38**		0.41**		0.41**		0.42**		0.16
		(0.16)		(0.16)		(0.17)		(0.17)		(0.22)
Government effectiveness		0.31		0.13		0.33		0.36		0.80**
		(0.24)		(0.24)		(0.23)		(0.23)		(0.35)
Fixed effects	Time	Time	Time	Time	Time	Time	Time	Time	Time	Time
Full specification	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	326	326	326	326	326	326	326	326	108	108
R^2	0.24	0.41	0.36	0.43	0.23	0.40	0.23	0.40	0.64	0.69
Adjusted R^2	0.23	0.39	0.35	0.41	0.22	0.37	0.19	0.38	0.62	0.66
Note:	*p<0.1; **p<0.05; ***p<0.01									

Table S7: **Growth regression, 10 year.** Panel Regression Models of ten-year growth between 1999-2009, 2004-2014, and 2009-2019, with explanatory variables of the five years prior: 1995-1999, 1999-2004, and 2004-2009 respectively. HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

J.3 20 year growth

	Dependent variable:							
	Twenty year growth, annualized							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP per capita, current USD, log	-1.45^{***}	-2.38^{***}	-1.58^{***}	-2.10^{***}	-1.38^{***}	-2.20^{***}	-1.05^{***}	-2.17^{***}
	(0.21)	(0.41)	(0.21)	(0.41)	(0.31)	(0.44)	(0.17)	(0.40)
HHI	-0.55^{***}	-0.10	-0.54^{***}	-0.16	-0.59^{***}	-0.18	-0.38^{**}	-0.23
	(0.15)	(0.27)	(0.14)	(0.27)	(0.15)	(0.29)	(0.19)	(0.29)
SkillInt	0.75^{***}	0.40^{*}						
	(0.21)	(0.24)						
Mean years of schooling			1.01^{***}	0.51^{**}				
			(0.19)	(0.23)				
ECI					0.56^{**}	0.07		
					(0.28)	(0.27)		
Fitness							0.46^{*}	-0.15
							(0.25)	(0.25)
Constant	2.51^{***}	2.51^{***}	2.51^{***}	2.51^{***}	2.51^{***}	2.51^{***}	2.51^{***}	2.51^{***}
	(0.14)	(0.13)	(0.13)	(0.13)	(0.15)	(0.13)	(0.15)	(0.13)
Population growth (annual %)		-0.04		0.24		0.06		0.04
		(0.40)		(0.43)		(0.41)		(0.41)
Pop, aged 0-14 (% of total pop)		-1.15^{**}		-1.24^{**}		-1.34^{**}		-1.42^{**}
		(0.58)		(0.62)		(0.60)		(0.58)
Tot. nat. res. rents (% of GDP)		-0.20		-0.22		-0.14		-0.15
		(0.34)		(0.34)		(0.36)		(0.36)
Urban pop (% of total pop.)		0.18		0.03		0.17		0.14
		(0.24)		(0.23)		(0.22)		(0.23)
Gross fixed cap form (% of GDP)		0.44^{**}		0.43^{***}		0.50^{***}		0.51^{***}
		(0.20)		(0.16)		(0.17)		(0.17)
Government effectiveness		0.12		-0.07		0.06		0.07
		(0.25)		(0.24)		(0.25)		(0.25)
Fixed effects	No	No	No	No	No	No	No	No
Observations	99	99	99	99	99	99	99	99
R^2	0.39	0.61	0.48	0.61	0.34	0.59	0.34	0.60
Adjusted R^2	0.37	0.57	0.46	0.58	0.32	0.55	0.32	0.55

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table S8: **Growth regression, 20 years.** Panel Regression Models of twenty-year growth between 1999 and 2019, explained by explanatory variables 1995 and 1999. HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

J.4 20 year growth, selected countries

	Dependent variable:									
	Twenty year growth, annualized									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP per capita, current USD, log	−1.81***	−2.44**	−1.98***	−2.11**	−1.84***	−2.19	−1.29***	−1.75	−1.59***	−2.11**
	(0.38)	(1.02)	(0.32)	(1.01)	(0.46)	(1.45)	(0.23)	(1.15)	(0.31)	(0.86)
HHI	−0.09	0.17	−0.24	0.21	−0.11	0.22	0.02	0.29	−0.16	0.07
	(0.19)	(0.50)	(0.23)	(0.57)	(0.26)	(0.65)	(0.16)	(0.53)	(0.22)	(0.63)
SkillInt	0.49	0.49								
	(0.30)	(0.35)								
Mean years of schooling			0.68***	0.74***						
			(0.21)	(0.22)						
ECI					0.38	0.28				
					(0.30)	(0.46)				
Output multiplier							0.39	0.27		
							(0.29)	(0.51)		
Fitness									−0.13	−0.20
									(0.34)	(0.31)
Constant	2.50***	2.50***	2.50***	2.50***	2.50***	2.50***	2.50***	2.50***	2.50***	2.50***
	(0.19)	(0.21)	(0.17)	(0.21)	(0.19)	(0.24)	(0.19)	(0.23)	(0.20)	(0.23)
Pop., aged 0-14 (% of total pop.)		−0.07		0.17		0.10		0.17		0.04
		(0.69)		(0.60)		(0.67)		(0.74)		(0.64)
Pop. growth (annual %)		−0.33		−0.08		−0.39		−0.45		−0.41
		(0.47)		(0.49)		(0.58)		(0.50)		(0.46)
Tot. nat. res. rents. (% of GDP)		−0.24		−0.47		−0.26		−0.22		−0.18
		(0.56)		(0.64)		(0.73)		(0.61)		(0.64)
Urban pop. (% of total pop.)		0.05		−0.30		−0.09		−0.17		−0.11
		(0.32)		(0.40)		(0.45)		(0.47)		(0.43)
Gross fixed cap form (% of GDP)		0.34*		0.25		0.39		0.28		0.37
		(0.20)		(0.24)		(0.27)		(0.35)		(0.27)
Government effectiveness		0.58		0.37		0.59		0.65		0.66
		(0.56)		(0.53)		(0.64)		(0.57)		(0.56)
Fixed effects	No	No	No	No	No	No	No	No	No	No
Observations	36	36	36	36	36	36	36	36	36	36
R^2	0.72	0.81	0.75	0.81	0.69	0.78	0.70	0.78	0.67	0.78
Adjusted R^2	0.69	0.75	0.73	0.75	0.66	0.70	0.67	0.71	0.64	0.70
Note:	*p<0.1; **p<0.05; ***p<0.01									

Table S9: **Growth regression, 20 years, selected countries.** Linear Panel Regression Models of twenty-year growth between 1999 and 2019, explained by explanatory variables 1995 and 1999, for a subset of countries for which Output multipliers are defined. HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

J.5 5, 10, 20-year growth: direct comparison of metrics

	Dependent variable:											
	5 year growth, annualized				10 year growth, annualized				20 year growth, annualized			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDP/c, log	−1.72*** (0.36)	−1.47*** (0.23)	−2.33*** (0.28)	−1.42*** (0.26)	−1.68*** (0.36)	−1.47*** (0.23)	−2.26*** (0.28)	−1.45*** (0.22)	−1.59*** (0.29)	−1.50*** (0.21)	−2.04*** (0.24)	−1.59*** (0.28)
HHI	−0.30 (0.20)	−0.22 (0.21)	−0.25* (0.14)	0.18 (0.14)	−0.37* (0.21)	−0.35 (0.23)	−0.31** (0.15)	0.05 (0.20)	−0.53*** (0.15)	−0.34* (0.18)	−0.44*** (0.12)	−0.01 (0.17)
SkillInt	0.57*** (0.22)	0.70*** (0.20)	0.66*** (0.21)	0.19 (0.23)	0.51** (0.22)	0.62*** (0.20)	0.57*** (0.21)	0.33 (0.20)	0.67*** (0.23)	0.70*** (0.21)	0.70*** (0.20)	0.44* (0.25)
ECI	0.53 (0.38)				0.42 (0.36)				0.25 (0.28)			
Fitness		0.31 (0.21)				0.16 (0.22)				0.36* (0.22)		
Yrs schooling			1.34*** (0.22)				1.27*** (0.23)				0.97*** (0.20)	
Output multiplier				0.65*** (0.24)				0.57*** (0.16)				0.32 (0.24)
Fixed effects	Time	Time	Time	Time	Time	Time	Time	Time	No	No	No	No
Observations	444	444	444	108	326	326	326	108	99	99	99	36
R^2	0.16	0.15	0.25	0.56	0.25	0.24	0.39	0.65	0.39	0.41	0.55	0.74
Adjusted R^2	0.15	0.14	0.24	0.53	0.23	0.23	0.38	0.63	0.37	0.38	0.53	0.70
Note:												*p<0.1; **p<0.05; ***p<0.01

Table S10: **Growth regression, direct comparison.** SkillInt is country skill intensity. Yrs schooling is mean years of schooling. HHI is the Herfindahl-Hirschman index. ECI is the economic complexity index. Robust standard errors clustered at the country level in brackets.

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5 Discussion and Conclusion

This thesis has sought to advance the understanding of path dependence in structural change for the green transition and beyond in three directions: green industrial strategy, labour markets, and the relationship between product diversification and human capital. The three papers have their own discussion sections contextualising their literature contributions, limitations and future directions. This concluding section of the thesis aims to add overarching learnings from applying networks to the study of structural change. I will first synthesise three insights that emerge across the different papers. Then, I will discuss the limitations of this work and point to some future research directions.

5.1 Emerging insights on pathways in the green transition and beyond

5.1.1 Local network interactions matter for structural change

Throughout this thesis, I have looked at systems where the local dynamics in the network matter for individual actors that bring about, or are affected by, structural change. These interactions on a network happen at a level between the micro- and macro-scale that is also sometimes called the 'meso scale' (Arthur, 2013; Dopfer et al., 2004). Arthur (2013) describes how out-of-equilibrium economic dynamics usually take place on the meso scale – people hear about job opportunities in their social network (Jackson, 2008), groups of companies linked together on the supply chain inadvertently cause systemic risk (Diem et al., 2022), and interacting traders create market bubbles and crashes (Arthur, 2013). As can be seen from these examples, networks are ideal tools for studying the meso scale. They show how parts of the system are connected and form the whole. For each paper, I will indicate the meso scale and explain how it matters.

Paper 1 shows the meso scale matters for green industrial strategy. Industrial strategy diffuses between related countries, products, and policy instruments. When introducing new industrial policies, countries follow related countries, target adjacent products, and use neighbouring instruments. What happens in 'faraway' parts of the network has less influence.

Paper 2 introduces the concepts of 'in-neighbours' and 'out-neighbours' for the set of jobs that are potential occupational transition options for workers. This set is important. What matters for individual workers and employers is not the overall state of the economy but the state of the economy in their subnetwork of neighbours. Staying in one's occupation is often the best strategy for displaced workers (Neffke et al., 2024), but having many options available outside one's occupation raises workers' wages and helps to manage the risks of labour market shocks (Moro et al., 2021).

Paper 3 adds to the product space literature by finding that countries often diversify into products with similar levels of skill intensity. Country-level export diversification often happens because countries build on their existing capabilities (Hidalgo, 2023). This leads to path dependencies, because higher-density product neighbours in the product space are more likely diversification options than products reached by larger leaps. We show that these neighbours are usually more aligned in terms of human capital requirements, connecting the literature on structural change with schooling and learning. We also show that more education can help countries increase the size of their meso scale of diversification options.

5.1.2 The interaction between the green transition and the network structure can create frictions

In networks where agents 'move' over the edges connecting nodes, certain network topology features can make it easier for bottlenecks and frictions to arise. However, these only materialise when the capacity or desirability of nodes is shocked in a particular way and agents are required to move. An important metric for this is assortativity. In assortative – or *homophilous* – networks, 'like connects to like' in some aspect. A fully assortative shock means that connected nodes are affected in the same way. In that case, any transition or pathway leads to a similar outcome and cannot alleviate the shock. Conversely, during a disassortative shock, nodes are just one transition away from a completely different situation, which can alleviate frictions quickly. Thus, the interplay between the network structure and the shock creates frictions.

In Paper 2, we show that the change in occupational demand from the decarbonisation of the power sector can be assortative on the occupational mobility network, increasing the potential for labour market frictions. This can have repercussions for inequality and the speed of the transition. We additionally show that the impact is not homogenous across occupations or time. Different phases of the green transition interact differently with the labour market network. Different kinds of frictions can thus impact the same occupation on the same network structure at different points in time.

In Paper 3, we show that skill intensity is assortatively distributed on the product space network. This may influence the development pathway of individual countries or their growth opportunities in technological transitions. While we do not discuss the implications of greening the economy in Paper 3, the green transition could thus lead to frictions when the desirability and availability of certain development paths change. Fossil fuel products may not have a good long-term growth perspective any more, whereas clean technologies do (Andres et al., 2023). This reevaluates which diversification pathways are desirable or not and can reshape the map of competitiveness (Bowen and Fankhauser, 2011). New winners and losers can arise based on their current network structure and potential for green spillovers (Fankhauser et al., 2013; Mealy and Teytelboym, 2022).

5.1.3 Path dependence can lead to inertia

Systems that exhibit path dependence can be hard to change course. This can be a good thing when the path brings prosperity (Goldstein et al., 2023). But it can be problematic when a system is headed for disaster or stagnation. For example, one of the path dependencies built in the earth-climate system is that rising temperatures lead to the release of CO_2 from permafrost, which leads to more warming (Koven et al., 2011). Similarly, in much of our economic system, fossil fuel infrastructure has 'locked-in' pathways towards more emissions (Fouquet, 2016), making it harder to decarbonise the economy than it would be otherwise.

All three papers show how inertia can arise due to path dependence. Paper 1 is the first study to show explicitly that path dependencies exist in green industrial strategy. This may constrain countries in their choice of policy. Implementing a hitherto unused policy that is not aligned with its policy portfolio according to the industrial strategy networks may be harder or more prone to failure due to network inertia. This can make more desirable policies suboptimal for certain situations. However, more research on the specific case study should be done to understand the actual level of risk involved. Furthermore, even with the additional risk of failure, pursuing the policy in certain situations may be worthwhile.

Paper 2 shows that inertia in career changes can lead to challenges and opportunities for workers at different points in time during a green transition. Because the demand shock is distributed assortatively, potential occupational switches are hard if outside options are also affected by the same shock. Displaced workers might not be able to transition towards vacancies fast enough, which can lead to both higher unemployment and a delayed transition due to unfilled vacancies. But, vice versa, we also show that the network can help alleviate frictions, especially in the initial phase of the transition when fossil fuel workers have opportunities in green construction. For example, workers in some occupations may face layoffs, but their skills can be in high demand for the green economy, leaving them with more opportunities than are available to the average worker.

In Paper 3, we build on earlier work on path dependence in the product space. Products with similar skill intensity levels are often connected in the product space. But rather than a core-periphery structure, which the literature finds for product-level *complexity* (Hidalgo et al., 2007), skill intensity divides the product space in two. An area of further study could be to look into whether 'moving towards the core' might, therefore, not always result in the best learning spillovers.

The presence of path dependence in a system does not mean that the future is pre-determined or that policy should further entrench it, but it does mean that policymakers should be aware that inertia may be present. Indeed, 'large leaps' of unrelated diversification are important for long-term development (Pinheiro et al., 2022), and pursuing them can be an optimal strategy because it expands subsequent diversification options (Alshamsi et al., 2018). This may well be true for green industrial strategy and certain career paths, too. And if you do decide to change course at some point, earlier is better, as path dependence implies that later adjustments are generally costlier (Aghion et al., 2019).

5.2 Future research and limitations of the network approach

Networks can be powerful analysis tools, but any network will be a simplification of the real world. I will first discuss the limitations of the principle of relatedness and adjacent possible approaches, followed by a discussion on two methodological limitations related to assumptions in network science: the networks' Markovian property and their transitory nature.

5.2.1 Limitations of the principle of relatedness and the adjacent possible approach

The networks in this thesis unveil dynamical processes of structural change. They do this imperfectly, however, as there are many other factors involved as well. Indeed, much of the variance in export diversification or green industrial policy adoptions in Papers 1 and 3 is explained by the fixed effects or remains unexplained by policy alignment, skill distance, or density. This is true for most applications of the principle of relatedness. Li and Neffke (2024) argue, therefore, that the principle of relatedness may be a poor guide for policymakers to 'pick winners'. Instead, they suggest using the principle of relatedness as a tool for growth diagnostics, which aims to understand the specific challenges holding back a country's development (Hausmann et al., 2008). In that context, the principle of relatedness can help policymakers find which industries are much smaller or more prominent in their country than one would expect. This way, rather than 'blindly' pursuing the statistical tools' suggestions, policymakers can try to address the underlying challenges directly (Li and Neffke, 2024).

For industrial strategy, there may be many different reasons why certain path dependencies exist. We find path dependence in policymaking along three dimensions: policy instruments, products, and countries. We discuss potential causes in the Introduction section of Paper 1 for the three dimensions of path dependence. These causes include constraints that may be hard to overcome and require years of experience, such as limited bureaucratic capacity. Others, such as tit-for-tat mechanisms, can quickly appear or disappear at the opportune moment. As we do not know a priori what drives the path dependencies, a cautious approach should be taken to derive implications for policymakers from this study. But our tools can be used by policymakers to scrutinise their novel policy ideas in light of potential 'anomalies' (c.f., Li and Neffke, 2024): are they in line with previous policies, and does the economic context make them more or less risky? Future research can try to understand the relationship between the path dependency channels and policy feasibility and success in more detail.

In Paper 2, likewise, occupational mobility is not just about skill or task similarity. The correlation between task or skill similarity and transition probability is not very high (Mealy et al., 2018; Frank et al., 2024), leaving much variation unexplained. One of the reasons is that economic pressures to fill the open vacancies may lead workers and employers to consider otherwise unlikely transitions – these pressures can change over time. The prospect of unfilled vacancies means that employers are keen to get training programs and on-the-job traineeships started to allow more occupations to be connected in the network. This may help alleviate frictions during the green transition as demand shifts and the labour market adapts. For example, according to Baruah (2019), 25% of those enrolled in the Wind Turbine Technician Program at Lethbridge College in Alberta (Canada) were former fossil fuel workers, even though this is deemed an unlikely transition in the literature. Vice versa, an unwillingness to move or commute for long distances can make workers change occupations towards those that are less related but more available locally. Future research can try to understand better how economic and social pressures influence labour market networks and use them to make better models for labour market outcomes. Either way, the network of skill-related occupations will remain important and could help design targeted training programmes or estimate how much help a particular region may need.

Similarly, the theory that capabilities drive diversification in the product space, promulgated in Paper 3, cannot explain all of its characteristics; other factors play important roles too (Li and Neffke, 2024). Indeed, industrial strategies to change the product diversification path beyond its natural course are the main topic of Paper 1. But finding the underlying drivers of structural change is complicated by data limitations in comparative international development. There are many moving parts, but just a hundred or so countries with a hundred-year time series. Compared to the possible ways in which countries can develop, this is unlikely to lead to robust inference (Durlauf et al., 2005). Diversification at a more local level, such as cities or subnational regions, can help provide further data (Li and Neffke, 2024; Rigby et al., 2022). Future research can also build on recent work that tries to understand better the relationship between structural change and the principle of relatedness and sophistication measures (e.g., McNerney et al., 2023; Bustos and Yıldırım, 2022; Li and Neffke, 2024). It is also important to understand when and why the principle of relatedness does not hold.

In all, the barriers to change that stem from the principle of relatedness and adjacent possible approaches in this thesis may or may not form obstacles in every case. They can, however, be a starting point for policymakers to investigate further to understand the risks of their approaches.

This thesis has also expanded the principle of relatedness into the new field of industrial strategy research. The principle of relatedness has already been shown to be widely applicable in economic geography (Hidalgo et al., 2018; Li and Neffke, 2024). It is intimately linked with ideas of path dependence (Arthur, 1994). Beyond economics, many social science literature strands report similar concepts (Goldstein et al., 2023). An open question for future research is the extent to which the principle of relatedness and path dependence is, more generally, a universal property of any social or economic system (Martin and Sunley, 2006).

5.2.2 Markovian property and multi-step path dependence

The Markovian, or memoryless, assumption that I make throughout this thesis implies that the network spreading processes only depend on the system's current state but not on earlier states. In Paper 2, for example, we define an occupational mobility network, where edges between occupations indicate workers' propensity to move from one occupation to the next. Now, imagine two workers who are employed as Sales Managers. One of them has a background in sales and was a Sales Representative before, and the other has a background in management and was a Construction Manager in a previous job. Surely, these histories matter for their likely next occupational move. The network, however, implies that while the current state matters, past states do not. This makes the analysis more tractable but is a simplification of reality. In the case of occupational transitions, looking at a slightly more abstract level, such as the knowledge, skills and ability (KSA) requirements rather than specific tasks of an occupation, could mitigate some of the risks of the Markovian assumption (Nedelkoska et al., 2018).

The Markovian assumption also means that all path dependencies in this thesis ignore histories more than one step away, as seen from the Sales manager example above. In the slightly different industrial strategy and product space networks, our frameworks cannot distinguish between different orderings of earlier-implemented policies or acquired product competitiveness. This can increase the uncertainty in our approach. Further analysis can use alternative novel methodologies, such as higher-order networks that can deal with non-Markovian networks directly (Scholtes et al., 2014; Scholtes, 2017). However, there may be trade-offs in clarity or data requirements. Occupational mobility networks can be constructed from surveys asking workers about their previous employment, a relatively common question in government labour market surveys. Higher-order networks, conversely, would require data on complete employment histories, which are usually not included in such surveys. Novel datasets such as online CV repositories can help here (Frank et al., 2024), although they will have limitations of their own.

5.2.3 Network transience

The networks I study in this thesis are assumed to have a fixed structure over time. This can be a valid assumption in the short run, particularly if the network structure changes relatively slowly compared to the flows on the network. But it can be a strong assumption for the long run. In the occupational network used in paper 2, for example, the current similarities between occupations are used for 2035. Of course, skill requirements and the content of jobs can change over time, influencing their position vis-à-vis other occupations. For example, Atalay et al. (2020) show that the job advert content of *cashiers* in the 1960s started out most similar to *cashiers*, but was more similar to *computer operators* in the 1970s, and to *accountants* in the 1990s. In addition, new nodes can arise when occupations that did not exist before become more prominent. These changes will affect the frictions that workers in specific occupations will face. Future work can try to understand these changes empirically and endogenise them in the model.

Similarly, the supply chain relations between industries can change over time as products and technologies are updated. For Paper 2, to understand the size of the problem, we tested the effect of using different input-output networks. We found that this effect was small.

In the case of policy sequences, Linsenmeier et al. (2022) find that carbon pricing often follows an extensive portfolio of different policy instruments. However, recent adopters were able to introduce carbon pricing quicker. While this may have to do with the policy spreading on the country network and thus becoming easier to implement by other countries (c.f., Paper 1), it could also signify a qualitative change in the policy instrument network. Further research can try to disentangle the two effects.

While the assumption of a fixed network structure is often made, there are ways to *endogenise* a dynamic network formation; for an early application of this to labour flow networks, see Fair and Guerrero (2023). Novel network frameworks, such as temporal networks, could also allow for more flexibility (Kim and Anderson, 2012). But the insight that endogenous network formation is important is not new. For example, the classic Padgett and Ansell (1993) showed how Cosimo de' Medici successfully changed the structure of the social network of 15th-century Florence by placing his family in its centre.

5.2.4 Alternatives to networks

There are alternatives to networks to model and visualise pathways and relationships in economic geography. Recently, *embedding* methods have become an alternative to represent distance and relatedness between different concepts. Embedding approaches place concepts – the *node* equivalent in networks – in high-dimensional spaces. The Euclidean or cosine distance between the concepts can be interpreted as a metric for relatedness – similar to *edge* weights. Networks can be changed into embeddings using network embeddings (Shi and Evans, 2023; Hou et al., 2020). Tacchella et al. (2023) apply network embedding to the product space and find that it outperforms the network-based methods for predicting product diversification. In an alternative approach, Börner et al. (2018) visualises a network of over 13,000 skills with community structure as a *map* (see also Gansner et al., 2010).

A classic alternative to networks for visualising a complex system's dynamics is a ball moving in a three-dimensional *energy landscape*. The ball follows a path towards a local minimum, where it is stable. The energy landscape knows many of these stable points, but some are more favourable than others. Perturbations and kicks to the ball or shifts to the energy landscape can move the ball towards a different equilibrium (Mealy et al., 2023). This image has been used in many disciplines to visualise complex systems, including climate science and climate policy literature. For example, Steffen et al. (2018, fig. 2) use this figure when discussing a runaway 'hothouse earth' climate system induced by a further rise in GHG emissions and a 'stabilised earth' alternative. Conversely, fig. 2 in Otto et al. (2020) show how 'social tipping interventions' can reshape the energy landscape, allowing the ball – visualised as the earth – to roll towards a 'decarbonised' state. Similarly, fig. 2 in Mealy et al. (2023) shows how 'sensitive intervention points' can move the ball from an unfavourable equilibrium onto a better trajectory. Energy landscapes are powerful mental models, but their quantitative use is limited. Networks represent a more tractable alternative and are easier to model.

5.2.5 Extensions of the network approach in this thesis to structural change

The papers presented in this thesis can all form the basis for further study, and each paper lists its own future research directions. Here, I propose a network-centric framework of modelling 'depth' and use that to suggest further research directions based on the question of structural change for the green transition. These suggestions go beyond individual studies and might require the scale of a research programme to be implemented.

I distinguish three levels of modelling depth of network spreading. In level 1, the network is described, and its nodes and edges are defined. The network can be used to explore the current state, and potential *next states* in the network can be identified, too. This level shows potential bottlenecks or opportunities that the network structure entails. The strength of this type of analysis comes from the fact that complex structures can be exposed with limited assumptions, but its predictive power over long time horizons may be limited. Most of my work falls in level 1.

Level 2 explores multiple steps into the future over time. This requires a further description of the time evolutionary process. That is, we need to pinpoint how an edge between nodes i and j with weight x translates into the propensity to transition from i to j between time t and $t+1$. This is often much harder. Consider the task-relatedness network of occupations in Moro et al. (2021). How does a skill overlap of 70% between two occupations translate into the likelihood of a displaced worker transitioning between them, given a level of unemployment and vacancies? This is a priori unclear and can only be tackled with additional assumptions or data on overall transition propensity and how that is distributed for different levels of task overlap. Level 2 can thus lead to a more powerful analysis than level 1 but requires additional assumptions and/or data and careful consideration of compounding uncertainty. It might take several years to get a level-2 study right.

A natural way to explore level 2 is with agent-based models (Axtell and Farmer, 2022; Farmer and Foley, 2009), but other modelling approaches can also be used. An example is the labour-market agent-based model from Del Rio-Chanona et al. (2020); Berryman et al. (2023).

Level 3 is a synthesizing step that quantifies how a network constrains relevant macroeconomic outcomes. In our case, this is the impact of path dependence in structural change on decarbonisation – in terms of, for example, decreased speed or higher levels of inequality. This requires connecting our level 2 models to macroeconomic models with explicit feedback mechanisms and might result in a model 'ecosystem', where several hard-linked model parts (e.g., on economic production, the labour market, policymaking) operate together and influence one another dynamically. A level 3 extension, if the right data exists, requires substantial resources and might take several researchers multiple years to get right (Santos Oliveira et al., 2024; Niet et al., 2022).

For each paper, I will give an example of how they can be extended towards levels 2 and 3. A level 2 follow-up to Paper 1 could develop an explicit model of industrial policy diffusion, providing potential trajectories for countries' green industrial strategy over time. This should answer the 'when' and 'where' of policy diffusion (Graham et al., 2013) and would include not only new policies popping up but also old ones disappearing. At level 3, the manufacturing capacity growth or product diversification potential of specific policies should be identified. This can also be negative due to trade wars and tit-for-tat mechanisms.[6] Policies can then be analysed for their potential to increase green diversification and manufacturing capacity, both directly and indirectly via diffusion.

A follow-up to Paper 2 can try to explicitly compute unemployment and unfilled vacancy trajectories by modelling how workers change jobs timestep by timestep. This would require additional analysis on how quickly people are able to start working in jobs that are to some degree related to their own. Empirically observed

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[6] This approach is somewhat similar to Linsenmeier et al. (2023)'s method of measuring carbon pricing diffusion and their emission reduction potential of Eskander and Fankhauser (2020)

transitions can help to infer job transition propensity for different occupations and skill levels. We do this in Berryman et al. (2023): using empirical job transition data and a structural change scenario for Brazil, we estimate levels of open vacancies and unemployment per occupation and region in Brazil. A level 3 analysis would go one step further and explicitly model the impact of unfilled vacancies and unemployment on firm-level output and taxation, which then feeds back into the economy, impacting country-level GDP, wages, labour demand *for the next year*, and the speed of the transition. An important question to set this up is how the scarcity of specific skills limits a firm's output. For example, if 10% of machine setter jobs in a paper-making firm are vacant but all other occupations are fully staffed, will it miss 10% of output in a Leontief way? Or can it be modelled with a CES-like production function, where other workers take over some of their tasks? And is this also true if the paper-making firm misses other types of occupations?

Paper 3 could be followed by a level-2 study that incorporates time in the product space (e.g., see O'Clery et al., 2021; Zaccaria et al., 2014) to understand the role of skill intensity and skill distance on export diversification speed. This study could examine how and when skills or learning spillovers become important. Recent studies that work on similar questions and methods, such as the 'Genotypic Product Space' (Schetter et al., 2024), can also be used as a basis for the level-2 study. At level 3, data on skill-enhancing policy or technological diffusion might help to understand if and how fast countries can acquire 'missing' skills. This analysis may help understand certain poverty traps, such as the middle-income trap, which relates to countries that have reached middle-income status without in time attaining high-income status (Agénor, 2017; Schetter et al., 2024). Are there specific patterns in acquiring skills and pursuing structural change in those countries that are different than in others that did succeed in attaining high-income status? Alternatively, potential time-sensitive pathways towards acquiring skills for green growth can be examined for countries with stranded dirty products (e.g., Andres et al., 2023; Fankhauser et al., 2013). The benefits or downsides of green industrial strategy can be made explicit in terms of diversification and diffusion of competitiveness and technological growth.

As the examples show, level 2 and 3 analyses quickly grow in complexity, data needs, and uncertainty. Future researchers will need to decide whether the investments in creating these models will be worthwhile (Niet et al., 2022).

Epilogue

Embarking on this DPhil has been a life-changing experience. I loved the opportunity to read widely on the different topics in this thesis. I hope to have contributed to the knowledge of structural change and path dependence. The new knowledge and capabilities I acquired during my DPhil will stay with me and shape my future. More than before, I realise that my network neighbours constantly influence my next moves, and I, vice versa, influence theirs. Many opportunities will be missed, but, conversely, every encounter at a conference may result in meeting a future co-author. I am excited to see where this will take me.

References discussion and conclusion

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