Journal of Financial Economics 147 (2023) 271–296

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Automation and the displacement of labor by capital: Asset pricing theory and empirical evidence☆

Jiří Knesl

Saïd Business School, University of Oxford, Oxford OX1 1HP, United Kingdom

ARTICLE INFO

Article history:
Received 8 February 2022
Revised 4 November 2022
Accepted 7 November 2022

JEL classification:
G10
G12
G30
G31
J24
O33

Keywords:
Automation
Technology shock
Technology adoption
Stock returns
Displacement
Risk premium

ABSTRACT

I examine the asset pricing implications of technological innovations that allow capital to displace labor: automation. I develop a theory in which firms with displaceable labor are negatively exposed to such technology shocks. In the model, firms optimally adopt technology to gain competitive advantage but in equilibrium competition erodes profits and decreases firm value. Empirically, I find that firms with high share of displaceable labor have negative exposure to technology shocks. A long-short portfolio sorted on this variable mimics macroeconomic measures of technology shocks. Negatively exposed firms earn a 4% annual return premium consistent with displacement risk from technological progress.

© 2022 The Author. Published by Elsevier B.V.
This is an open access article under the CC BY license
(http://creativecommons.org/licenses/by/4.0/)

1. Introduction

Technological advances over the last four decades have led to adoption of many new technologies (Jovanovic and Rousseau, 2005). An important subset of these innovations, for example robots and software, focus on *automation* that displaces human labor in favor of machine capital (Acemoglu and Pascual, 2020; Autor et al., 2003). The large-scale displacement of routine-task labor by technology, and the resulting society-wide impacts have been termed *"The Second Machine Age"* (Brynjolfsson and McAfee, 2014). This naturally raises the question of how automation affects asset prices.

I study whether displaceable labor affects firms' value and their exposure to technology shocks. The amount of routine tasks which can be automated varies across

☆ Dimitris Papanikolaou was editor for this article and I thank him and the anonymous reviewer for helpful guidance. I am indebted to my committee members: Adlai Fisher, Lorenzo Garlappi, Jan Bena, Murray Carlson, and Jesse Perla for their guidance and support. Further, I thank Jack Favilukis, Boyan Jovanovic (discussant), Leonid Kogan (discussant), Stavros Panageas, L'uboš Pástor, Carolin Pflueger, Lawrence Schmidt (discussant), Harald Uhlig, seminar participants at the University of Rochester, the University of California at San Diego, the University of Washington, University of Oxford, the University of Amsterdam, BI Norwegian Business School, Stockholm School of Economics/Swedish House of Finance and conference participants at the EFA 2021, the Utah Winter Finance Conference 2020, Adam Smith Junior Workshop 2019, CFEA 2019, ESSEC Nonstandard Investment Choice Workshop 2019, NFA 2019, CICF 2019, the Belgrade Young Economists Conference 2019, IRMC 2019, Yale Doctoral Fall Finance Conference 2018, the Macro Financial Modeling Summer Session at the Becker Friedman Institute 2018, UBC Finance Summer Conference 2018 and FMA Doctoral Consortium 2018 for valuable comments.

E-mail address: jiri.knesl@sbs.ox.ac.uk

https://doi.org/10.1016/j.jfineco.2022.11.003
0304-405X/© 2022 The Author. Published by Elsevier B.V. This is an open access article under the CC BY license
(http://creativecommons.org/licenses/by/4.0/)

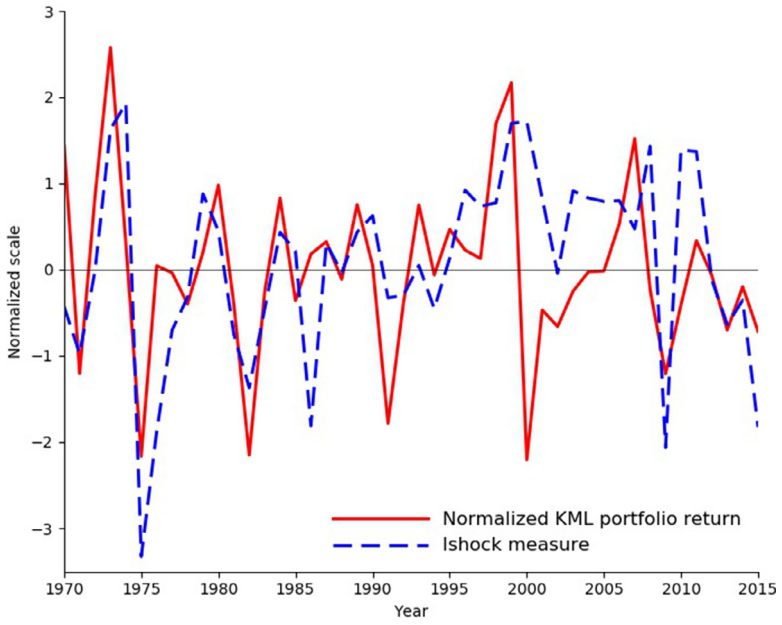


Fig. 1. Technology shocks (I-shock) and low AP minus high AP firms. The figure plots the I-shock measure (dashed blue line) and the annual return of the zero-cost (KML) portfolio (solid red line). The I-shock measure is based on changes in quality-adjusted relative price of capital goods. The KML portfolio has a long (short) position in firms with low (high) share of displaceable labor, i.e., the bottom (top) quintile of firms ranked by the AP measure. The underlying portfolio returns are value weighted. Both time-series are plotted at annual frequency and are normalized to mean zero and standard deviation of one. The sample period is from 1970 to 2015.

occupations and thereby across industries (Autor and Dorn, 2013). Empirically, I find that firms with a *high* share of displaceable labor have more *negative* exposure to technology shocks. A long-short portfolio of firms sorted on their share of displaceable labor replicates the dynamics of price changes of capital goods (Fig. 1), thus creating a connection between a macroeconomic variable and the dynamics of stock returns. Further, firms negatively exposed to technology shocks earn a premium of about 4% per year.

To understand these findings, I develop a general equilibrium model of optimal technology adoption with heterogeneous firms that monopolistically compete in product markets, and heterogeneous households that experience uninsurable idiosyncratic labor-income shocks. In the model, all firms within a given industry have the same opportunity to adopt technology. While automation can be beneficial for an individual firm, it entails adoption cost. In equilibrium, firms compete the benefits away being left with the costs. As a consequence, a technology shock that facilitates automation decreases profits and market value of firms that can replace labor by capital. The mechanism depends on the degree of competition between firms. Higher competition strengthens the negative effect on firm value, while lower competition weakens it.[1]

In my model, a firm's profit depends on its product price relative to the product prices of its competitors. This induces a strategic element in a firm's technology adoption. Because automation lowers a firm's product price relative to its competitors and increases its revenues by taking it from its competitors, upon the occurrence of a technology shock each firm in the industry has an incentive to automate despite the adoption cost. These benefits deteriorate as the number of automated firms in the industry increases and the lower product prices become less of a competitive advantage. As a consequence, automation does not provide an advantage but is a costly necessity to stay competitive. Assuming all firms in an industry start with the same production technology, a symmetric Nash equilibrium of optimal automation exists.[2] I show that in equilibrium, technology shocks lead to lower profits and firm value.[3] Firms with displaceable labor have negative exposure to such technology shocks consistent with empirical evidence.

An appealing feature of the model is its flexibility to generate both positive and negative price of technology shocks. The sign of the price of risk depends on the variance of individual workers' future labor productivity. The adoption of capital-based production reallocates workers from old to new occupations. Although *on average* all

[1] Although not shown in my model, the effect of automation would be positive in the case of monopoly.

[2] Firms within industry have similar share of displaceable labor measured by my AP variable defined later. About 78% of cross-sectional variation in this variable is due to between-industry differences and only about 22% due to within industry differences. The dominating between-industry variation is the focus of my model and for tractability reasons I abstract from the minor within-industry variation.

[3] This is different from Greenwood and Jovanovic (1999); Hobijn and Jovanovic (2001), where firm value decreases because of incumbents' inability to adopt new technology and from Pástor and Veronesi (2009), where firm value decreases because of change in the nature of risk. In my model the value of firms decreases as firms strategically adopt technology but eventually compete away the potential rents.

workers will be more productive in their new occupations, an *individual* worker experiences either an increase or a decrease in his or her productivity. The labor productivity shocks are purely idiosyncratic and realized only once the worker moves to the new occupation. Since the idiosyncratic shocks are triggered by the aggregate technology shocks and markets are incomplete, the idiosyncratic risk affects the premium of the aggregate technology shock. If the variance of the individual labor productivity shocks is low, households do not fear a technology shock as the shock generates improvements for all households. If the variance of individual workers' productivity increases, households dislike technology shocks as some of them may lose large parts of their labor income. This result highlights the importance of imperfect risk sharing (Constantinides and Duffie, 1996) and particularly its relationship to technological progress as described in Kogan et al. (2020), and Gârleanu and Panageas (2017).

Empirically, I measure a firm's share of displaceable labor by a ratio of labor that can be easily substituted by capital (numerator) and the firm's current capital stock (denominator), and denote it Automation Potential (AP). To construct this measure, I classify employees' occupations by the routine intensity of their tasks using occupational characteristics from the O*NET database and merge the occupational data with firm data for employment and capital stock from Compustat.[4] The share of displaceable labor is predominantly an industry-level characteristic. The variation between industries explains more than 70% of the total cross-sectional variation in the share of displaceable labor measured by AP.

I use changes in quality-adjusted relative prices of capital goods as an empirical measure of technology shocks.[5] The theoretical foundation of this measure has been shown in previous literature (e.g., Cummins and Violante, 2002; Hornstein and Krusell, 1996) and is based on the idea that improvements in the production of capital goods such as machines and software make capital goods more accessible and are reflected in lower prices of these goods adjusted for changes in quality.[6] As an additional measure of technology shocks, I use relative productivity shocks of automation-capital producing industries. I verify that the changes in quality-adjusted prices of capital goods are associated primarily with relative productivity growth of these automation-capital producing industries.

My paper is related to Papanikolaou (2011), who uses stock prices as a measure for technology shocks embodied in capital. Using a two-sector general equilibrium model, he shows that relative stock prices of *producers* of capital goods are informative about capital-embodied technology shocks. I take a different approach and develop a theory where stock returns of different (actual vs. potential) *users* of capital are informative about these technology shocks. Applying this approach to the U.S. data reveals a strong comovement between stock prices of firms with displaceable labor and relative prices of capital goods that has not been documented in previous studies. Hence, my approach complements the methodology in Papanikolaou's paper.

I further show that the technology shocks measured by the changes in quality adjusted relative prices of capital are a state variable indicating the risk of labor income for households. Assets that co-move with this state variable are expected to earn a return premium. Excess returns are highest for firms with a strong negative exposure and decrease across the portfolios toward firms with a weak exposure. Size, growth opportunities (book-to-market ratio) and other cross-sectional predictors do not explain the premium in firm-level Fama–MacBeth regressions. The return premium is, however, explained by technology shocks. This finding is reminiscent of Kogan and Papanikolaou (2014), however, they focus on pricing the dimension of growth opportunities, while I focus on the dimension of labor displacement, hence documenting a new role of technology shocks in the cross-section of returns.

More generally, my paper relates to the broad literature on pricing capital-embodied technology shocks, e.g., Papanikolaou (2011); Garleanu et al. (2012); Garlappi and Song (2017); Kogan et al. (2020). I add to this literature by focusing on labor displacement by capital. Empirically, I show that labor-displacement risk closely relates to a measure of capital-embodied technology shocks and theoretically, I rationalize the expected return premium through idiosyncratic labor-income risk in incomplete markets.[7]

This paper is also related to two other streams of literature: First, a number of studies have examined the importance of technology shocks embodied in capital for economic growth, e.g., Greenwood et al. (1997); Kogan and Papanikolaou (2014). This literature emphasizes that technology shocks increase the efficiency of investment and thereby stimulate investment in growth opportunities. A second line of research focuses on the ability of new types of capital to carry out tasks that used to be performed by human workers. For example, Autor et al. (2006); Autor and Dorn (2013) link the shifts in labor force across occupations and the employment and wage polarization to the spread of new technologies. I show that technology shocks embodied in capital affect firms not only through investment in growth opportunities, but also through their ability to substitute for labor in performing tasks, where it is technically feasible. Hence, technology shocks are important for *labor-intensive* firms with displaceable labor. To the best of my knowledge, this study is first to draw the link between capital-embodied technology shocks and stock returns of these firms.

[4] O*NET database is the primary source of occupational information in the U.S. It provides a comprehensive set of occupational characteristics such as required skills and abilities or importance of various tasks. It is administered by the U.S. Department of Labor/Employment and Training Administration through the O*NET Resource Center. Data from its predecessor (Dictionary of Occupational Titles) are incorporated in the first releases of the O*NET database.

[5] See Greenwood et al. (1997, 2000); Fisher (2006).

[6] I validate this assumption using data from the NBER-CES Manufacturing Industries database and the Input-Output Accounts from the U.S. Bureau of Economic Analysis.

[7] The implications of uninsurable idiosyncratic labor-income risk have been addressed in several prominent studies, e.g., Constantinides and Duffie (1996); Constantinides and Ghosh (2017); Schmidt (2016). The effects of technological growth in the presence of imperfect risk sharing are examined in, e.g., Gârleanu et al. (2012); Gârleanu and Panageas (2017).

Zhang (2019) uses a different measure of displaceable labor while studying stock returns. Zhang does not examine the effect of technological change on the cross-section of expected stock returns, but instead analyzes firms' exposures to aggregate market risk and explicitly states that technology shocks do not play a central role in his analysis.[8] Online Appendix 1 provides a detailed comparison.

The paper contains main results, and an Online Appendix includes extensions and further technical details. I refer to some of them throughout the text.

2. The model

I develop a two-period general equilibrium model that illustrates how technology shocks affect asset prices through stimulating labor displacement and technology adoption.

2.1. Firms, technology, and automation

The economy exists for two periods. Production consists of two sectors $s \in \{1, 2\}$. Sector $s = 1$ initially consists of labor-based firms and sector $s = 2$ of capital-based firms. Firms in sector $s = 1$ can automate as described in more detail below.

Within each sector s, there is a mass 1 of a continuum of firms, indexed by $f \in [0, 1]$, that produce firm-specific differentiated goods $Y_{f,s,t}$ at time t and compete monopolistically. Since firms are atomistic, each can abstract from the consequences of its choices for the sector level aggregates defined by CES aggregators below and competitive equilibrium can exist (Aumann, 1964; 1966). Firms produce their goods with a linear production function, which is either labor-based, $Y^l_{f,s,t} = L_{f,s,t}$, or capital-based, $Y^k_{f,s,t} = K_{f,s,t}$. A firm with capital-based production buys sector-specific capital $K_{f,s,t}$ at price $P^l_{s,t}$. I assume that firm's capital is active and fully depreciates in the period of investment.[9] The cash flow of a capital-based firm is

$$CF^k_{f,s,t} = P^k_{f,s,t} Y^k_{f,s,t} - P^l_{s,t} K_{f,s,t}, \tag{1}$$

where $P^k_{f,s,t}$ denotes the price of firm-specific good produced in a capital-based production. A firm with labor-based production hires sector-specific labor $L_{f,s,t}$ at sector-specific wage $W_{s,t}$. Labor-based firms have an option to automate by adopting capital-based production and paying automation cost κ.[10] Firms optimally automate when the price of capital investment $P^l_{s,t}$ becomes low enough. The cash flow of a firm with labor-based production is

$$\begin{aligned} CF^l_{f,s,t} &= P^l_{f,s,t} Y^l_{f,s,t} - W_{s,t} L_{f,s,t} \quad \text{if not automated} \\ CF^k_{f,s,t} &= P^k_{f,s,t} Y^k_{f,s,t} - P^l_{s,t} K_{f,s,t} - \kappa \quad \text{if automating,} \end{aligned} \tag{2}$$

where $P^l_{f,s,t}$ and $P^k_{f,s,t}$ are the prices of the firm-specific good.

Sector-specific capital, $K_{s,t}$ (i.e., total capital supplied to relevant firms in sector s), is produced competitively in a linear production function with an aggregate capital-embodied technology level A_t and sector-specific labor $L^k_{s,t}$ that is employed in production of capital:

$$K_{s,t} = A_t L^k_{s,t}. \tag{3}$$

Installation of capital is subject to decreasing returns to scale at the total amount of sector-specific capital as described in Eq. (4) and the capital is installed at cost.[11] The assumption of decreasing returns to scale $0 < \alpha < 1$ allows to generalize the equilibrium outcome to encompass not only pure-strategy but also a mixed-strategy equilibrium described below, but itself is *not* important for the final implications for stock returns.

$$I_{s,t} = K^{\alpha}_{s,t} \quad \text{where} \quad I_{s,t} = \int_0^1 K_{f,s,t} df. \tag{4}$$

The capital production and installation imply that individual firms face capital prices:

$$P^l_{s,t} = \frac{1}{A_t} W_{s,t} I^{\frac{1-\alpha}{\alpha}}_{s,t}. \tag{5}$$

Eq. (5) shows that an increase in technology A_t decreases the effective price of capital investment.[12] The technology A_t and the total amount of sector-specific investment determine the marginal cost of capital-based production relative to the marginal cost of labor-based production. Automation becomes favorable when the marginal cost of capital-based production decreases relative to the marginal cost of labor-based production.

Technology A_t is subject to a capital-embodied shock that is realized at the beginning of the second period. Specifically, I assume an initial level of technology A^{Low} that can increase to A^{High} with probability p_H as described in (6).

$$A_1 = A^{Low}, \quad A_2 = \begin{cases} A^{Low}, & \text{with probability} \quad 1 - p_H \\ A^{High}, & \text{with probability} \quad p_H \end{cases} \tag{6}$$

[8] Zhang (2019), page 1803: "The last reason for caution is that, for simplicity, my model assumes that labor and machines are two comparable input factors with fixed prices."

[9] This implies that firms cannot trade capital among themselves. Capital reallocation and spread of new technology through mergers and acquisitions has been studied by Jovanovic and Rousseau (2002, 2008) and reallocation of used capital by Eisfeldt and Rampini (2006, 2007). Trade in capital between firms across sectors can be optimal in a scenario when labor-based firms would benefit from acquiring capital from capital-based firms. I assume that capital is sector-specific so that firms cannot trade capital across sectors even if it didn't fully depreciate. I thank Boyan Jovanovic for pointing out this mechanism.

[10] This adjustment cost represents losses associated with the change of production technology such as, e.g., installation cost, learning to use new technology, or more broadly losses from production interruptions. In this sense, it is incurred by the firm and does not accrue to other entity in the model.

[11] This model emphasizes a different channel than Papanikolaou (2011), where stock prices of capital goods producers are informative about technology shocks. I leave this channel out by assuming perfect competition among capital producers and installation of capital at cost. Further discussion is in Online Appendix.

[12] This is despite the *partially* offsetting effect from the higher sector-level investment due to decreasing returns to scale ($\alpha < 0$). Although decreasing return to scale helps generalize equilibrium outcomes to encompass mixed-strategy equilibria, it is not the main driving mechanism, and these equilibria themselves are *not* necessary for the key asset pricing implications discussed later.

A technology shock $A^{Low} \rightarrow A^{High}$ decreases the price of capital investment $P^I_{s,2}$ in both sectors. Allowing only a positive technology shock in the model is not restrictive. The model can be easily extended to allow for a negative technology shock. The assumption of constant or improving technology implies constant or decreasing prices of capital investment. This is generally consistent with empirical evidence as the quality adjusted relative prices of capital goods experienced a secular decrease over the last four decades (Fisher, 2006; Cummins and Violante, 2002).

The firm-specific goods, $Y_{f,s,t}$, are combined to sector-specific goods, $Y_{s,t}$, using a constant-elasticity of substitution (CES) function (see Eq. (A.1) in Appendix A) with elasticity of substitution parameter ν. I assume $\nu > 1$, which implies that the firm-specific goods are imperfect substitutes to each other. The prices of the sector-specific goods, $P_{s,t}$, can be expressed using prices of firm-specific goods, $P_{f,s,t}$, (see Eq. (A.2)). The sector goods are combined to an aggregate final consumption good, $Y_{C,t}$, using a CES function with a different elasticity of substitution ρ (see Eq. (A.4)). I choose the aggregate consumption goods as a numeraire by setting its price $P_{C,t} \equiv 1$, and assume that $\frac{\nu-1}{\nu} > \frac{\rho-1}{\rho}$. This assumption implies that firm-specific goods within a given sector are closer substitutes than sector-specific goods (Broda and Weinstein, 2010). For example, individual products in food industry substitute each other more readily than all food products substitute products of a different industry such as car manufacturing.

Firms within each sector produce differentiated varieties and compete monopolistically. Given the production type, firms maximize dividends by setting the price of their goods:

$$D^l_{f,s,t} = max_{P^l_{f,s,t}} \{P^l_{f,s,t} Y^l_{f,s,t} - W_{s,t} L_{f,s,t}\}$$
$$\text{where} \quad Y^l_{f,s,t} = \left(\frac{P^l_{f,s,t}}{P_{s,t}}\right)^{-\nu} Y_{s,t} \tag{7}$$

$$D^k_{f,s,t} = max_{P^k_{f,s,t}} \{P^k_{f,s,t} K_{f,s,t} - P^l_{s,t} K_{f,s,t}\}$$
$$\text{where} \quad Y^k_{f,s,t} = \left(\frac{P^k_{f,s,t}}{P_{s,t}}\right)^{-\nu} Y_{s,t}, \tag{8}$$

where $Y^l_{f,s,t}$ and $Y^k_{f,s,t}$ are the demand functions for the firms' goods. The first order conditions of firms' optimization in (7) and (8) imply that firms charge constant markups over the marginal production cost (see (A.6)).

Upon the realization of the technology shocks at the beginning of $t = 2$, firms in the labor-based sector $s = 1$ decide whether to automate the production. Automation changes the labor-based production to capital-based production by incurring automation cost κ:

$$D_{f,1,2} = \max\{D^l_{f,1,2},\ D^k_{f,1,2} - \kappa\} \tag{9}$$

The fact that all firms in sector $s = 1$ are originally labor-based and operate in a symmetric monopolistic competition implies that all firms within this sector have equal incentive and opportunity to automate. This setup focuses on the *within-industry* competition and *between-industry* differences in firms' automation potential. The empirical analysis in later sections shows that these two characteristics play the primary role in firms' exposure to technology shocks.

Automation changes the firm composition as well as the use of labor within the sector. $\delta = \int_0^1 \mathbb{1}\{Automate = Yes\}_f df$ denotes the percentage of firms in sector $s = 1$ that decide to automate. Automation shifts labor from the direct production of firms' goods to the production of the sector-specific capital. $L^l_{1,2} = \int_0^1 L_{f,1,2} \mathbb{1}\{Automate = No\}_f df$ is sector $1's$ labor that is employed directly in labor-based firms. $L^k_{1,2} = \frac{1}{A_2}\left(\int_0^1 K_{f,1,2} \mathbb{1}\{Automate = Yes\}_f df\right)^{\frac{1}{\alpha}}$ is sector $1's$ labor that is employed in the production of the sector-specific capital. The total amount of labor in sector $s = 1$ is $L_{1,2} = L^l_{1,2} + L^k_{1,2}$.

2.2. Households

There is a large number, N_h, of ex-ante identical households.[13] Each household consists of two spouses, each of which supplies labor effort to a different sector. Households derive utility from consumption $c_{h,t}$ and disutility from labor effort $H_{h,1,t}$ and $H_{h,2,t}$ according to a utility function in the spirit of Greenwood et al. (1988):

$$U\left(c_h, H_{h,1}, H_{h,2}\right) = \mathbb{E}\Bigg[\sum_{\tau=t}^{2} \frac{\beta^{\tau-t}}{1-\gamma} \times \left(c_{h,\tau} - \chi \frac{H^{1+\theta}_{h,1,\tau}}{1+\theta} - \chi \frac{H^{1+\theta}_{h,2,\tau}}{1+\theta}\right)^{1-\gamma}\Bigg], \tag{10}$$

where β is households' subjective discount factor, χ governs the disutility of labor effort, γ is the coefficient of risk aversion, and $\frac{1}{\theta}$ is the Frisch elasticity of labor supply. Assuming households with two spouses simplifies the model as all households have, through their two spouses, exactly the same exposure to labor-income risks in each sector. This approach allows to easily embed idiosyncratic labor-income risk.

The labor effort $H_{h,s,t}$ transforms to $L_{h,s,t} = H_{h,s,t}$ effective hours of labor unless the spouse shifts from working directly in a labor-based firm to working in the production of sector-specific capital. If the spouse has to move to the production of sector-specific capital, the labor effort transforms to $L_{h,1,2} = (1 + \tilde{\epsilon}_h) H_{h,1,2}$ effective hours of labor. $\tilde{\epsilon}_h$ is the spouses' idiosyncratic random variable that determines their labor productivity when they move to the new job. This shock can be interpreted as a persistent shock to individual human capital. To keep simplicity, the job movements are purely intra-sectoral. When firms in sector $s = 1$ automate by adopting capital-based production, a corresponding number of spouses will be displaced from these firms and employed in the production of sector-specific

[13] Although not necessary, the households can also be defined as atomistic in a continuum $h \in [0, 1]$. However, it is assumed that the number is large enough to apply law of large numbers as in Constantinides and Duffie (1996); Constantinides and Ghosh (2017).

capital within the same sector $s = 1$.[14] The spouses cannot observe their idiosyncratic labor productivity $\tilde{\epsilon}_h$ until they are employed in the new job. The assumption of a shock to households' earnings, ϵ_h, following job displacement is motivated by empirical evidence in a number of studies (e.g., Stevens, 1997; Topel, 1990; Topel, 1991; Jacobson et al., 1993). These studies document large, persistent and generally adverse shocks to earnings from job displacement. I specify the distribution of the idiosyncratic labor productivity by:

$$\tilde{\epsilon}_h = \begin{cases} -\epsilon & \text{with probability} \quad p_\epsilon \\ +\epsilon & \text{with probability} \quad 1 - p_\epsilon \end{cases} \qquad \text{where } 0 < \epsilon < 1. \tag{11}$$

Markets are incomplete in the sense that households cannot trade an asset that would fully insure them against the realization of the idiosyncratic labor productivity. This framework of households and their income is analogous to Constantinides and Duffie (1996). Individual households are ex-ante representative, but exhibit ex-post heterogeneity in form of uninsurable permanent labor-income shock.

I deliberately choose the idiosyncratic labor productivity shock as mean preserving spread. This keeps the sector's supply of effective hours of labor independent from the idiosyncratic labor productivity shocks. The possible realizations of positive values of ϵ_h reflect the idea that technology shocks create also better job opportunities. This is widely consistent with the literature documenting the polarization of the U.S. labor market (e.g., Autor et al., 2003; Autor and Dorn, 2013). The use of a symmetric risk allows to focus only on the effect on households' utility from possible dispersion of this shock similar to Constantinides and Duffie (1996).[15]

To maximize their utility, each household solves following problem:

$$\begin{aligned} &\max_{c_{h,t}, H_{h,1,t}, H_{h,2,t}} U\left(c_{h,t}, H_{h,1,t}, H_{h,2,t}\right) \\ &\text{s.t.} \quad c_{h,t} = D_{h,t} + L_{h,1,t} W_{1,t} + L_{h,2,t} W_{2,t}, \end{aligned} \tag{12}$$

where $D_{h,t} = \frac{1}{N_h}\left(\int_0^1 D_{f,1,t} df + \int_0^1 D_{f,2,t} df\right)$ is the households capital income. The first order condition determines the optimal labor effort, $H_{h,s,t}$, as a function of wage (see (A.7)). The total supply of labor to sector s at time t is $L_{s,t} = \sum_{h=1}^{N_h} L_{h,s,t}$. The symmetry of the distribution of $\tilde{\epsilon}_h$ ensures that the labor effort of spouses working in capital production in sector $s = 1$ at $t = 2$ is transformed to effective hours on average in the same way as the labor effort of spouses working directly in labor-based firms in the same sector, $\mathbf{E}[L_{h,1,2}] = \mathbf{E}[(1 + \tilde{\epsilon}_h) H_{h,1,2}] = H_{h,1,2}$.

[14] Assuming purely intra-sectoral labor reallocation is not essential for the economic mechanism.

[15] This is a conservative approach, since the focus will be on a negative risk premium for the aggregate technology shock. A negatively skewed distribution of ϵ_h, which would account for large negative income shocks, e.g., job loss as documented in Knesl (2018), would increase the magnitude of this risk premium.

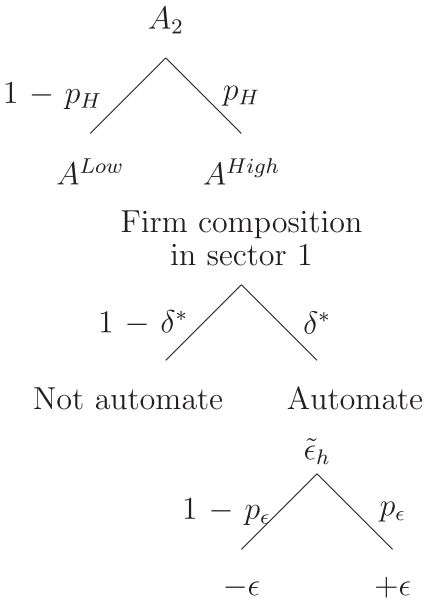


Fig. 2. Households' possible states.

The utility optimization gives a household-specific stochastic discount factor of the form:

$$\Lambda_h = \beta \left(\frac{c_{h,2} - \chi (1+\theta)^{-1} \left(H_{h,1,2}^{1+\theta} - H_{h,2,2}^{1+\theta} \right)}{c_{h,1} - \chi (1+\theta)^{-1} \left(H_{h,1,1}^{1+\theta} - H_{h,2,1}^{1+\theta} \right)} \right)^{-\gamma}. \tag{13}$$

Since all households are identical ex ante, the stochastic discount factors are identical across all households. Each single household prices assets in the same way. At the same time, aggregate consumption and labor efforts are not sufficient statistics for pricing firms as they omit the idiosyncratic component of households consumption due to the realization of the idiosyncratic labor productivity shock.

2.3. Valuation and equilibria

Firm values at $t = 1$ are given by:

$$\begin{aligned} V_{f,s,1}^l &= D_{f,s,1}^l + \mathbf{E}\left[\Lambda_h D_{f,s,2}\right] \quad \text{for } s = 1, \text{and} \\ V_{f,s,1}^k &= D_{f,s,1}^k + \mathbf{E}\left[\Lambda_h D_{f,s,2}^k\right] \quad \text{for } s = 2. \end{aligned} \tag{14}$$

The expectation operator in the valuation Eq. (14) is defined from household h's perspective over both aggregate and idiosyncratic states. The realization of all states and the corresponding probabilities are depicted in Fig. 2. The stochastic discount factor Λ_h takes a different value in each possible realization including the realization of idiosyncratic labor productivity risk $\tilde{\epsilon}_h$. Hence the households' idiosyncratic risk affects the valuation of assets. The idiosyncratic risk is relevant only when A^{High} is realized. The importance of the idiosyncratic risk is then given by the percentage of firms that automate δ^*. Hence the idiosyncratic risk is state dependent as in Constantinides and Ghosh (2017).

The equilibrium is defined by the solution of the households' optimization problem (12), firms' optimization (7)–(9) and market clearing conditions on all markets. The

market clearing conditions for product markets at the level of firms and sectors as well as for capital and labor markets are stated in Appendix A.

At $t = 2$, a further condition for a Nash equilibrium in sector $s = 1$ is that each firm must prefer its choice of production given choices of other firms in the sector. I define:

$$\Pi^k_{f,1,2} = \frac{1}{\nu} P^k_{f,1,2} \left(\frac{P^k_{f,1,2}}{P_{1,2}(\delta^*)} \right)^{-\nu} Y_{1,2}(\delta^*) - \kappa \tag{15}$$

$$\Pi^l_{f,1,2} = \frac{1}{\nu} P^l_{f,1,2} \left(\frac{P^l_{f,1,2}}{P_{1,2}(\delta^*)} \right)^{-\nu} Y_{1,2}(\delta^*), \tag{16}$$

where δ^* is the equilibrium percentage of automating firms, and $P_{1,2}(\delta^*)$ and $Y_{1,2}(\delta^*)$ are defined in (A.11a) and (A.11b), respectively. Expression (15) shows the payoff of a firm switching to capital-based production. This payoff consists of dividend and automation cost. Eq. (16) is the dividend of a firm that keeps labor-based production. Depending on the magnitude of the shock, an equilibrium of one of the following three types exists.

With no technology shock (i.e., $A_t = A^{Low}$), no firm in sector $s = 1$ prefers automation (**equilibrium 1**). The sector remains homogeneous with labor-based firms only, and inequality $\Pi^k_{f,1,2} \leq \Pi^l_{f,1,2}$ holds. With an incremental shock, **equilibrium 2** exists, where a percentage $0 < \delta^* < 1$ of firms in the sector automates and pays automation cost. It is defined by equality $\Pi^k_{f,1,2} = \Pi^l_{f,1,2}$, i.e., firms are indifferent between automating and keeping labor-based technology. This equilibrium can be thought of as a mixed-strategy equilibrium where firms choose an optimal probability δ^* to automate and probability $1 - \delta^*$ to keep the labor-based production. Automating firms extract higher rents at the cost of not-automating firms but incur also adoption costs. A large shock can lead to **equilibrium 3**, where all firms automate, i.e., $\delta^* = 1$. It exists when the price of capital $P^l_{1,2}$ is low and inequality $\Pi^k_{f,1,2} \geq \Pi^l_{f,1,2}$ holds. A firm would experience dramatically lower sales by keeping labor-based production given all other firms automated. Hence, all firms optimally automate despite mutually competing away the revenue advantage and incurring the adoption cost to avoid more severe punishment through lower sales.

Fig. 3 show the market-clearing product prices (Panel A), firm's revenues (Panel B), and dividends (Panel C) as functions of the fraction of automating firms δ (x-axis) for examples of the three types of equilibria indicated by column headings. With no shock (first column), the product prices of labor-based firms are below the product prices of automating firms everywhere except at $\delta = 0$. Accordingly, an automating firm would face lower demand for its products than labor-based firms regardless of how many firms automate except at $\delta = 0$. The dividend of a firm would be lower when it automates than when it does not due to the lower demand and would decrease further after accounting for the adoption cost as shown in Panel C. As a result, no firm has an incentive to automate, which leads to equilibrium 1 with $\delta^* = 0$.

An incremental shock can make a limited mass of firms $\hat{\delta}$ more competitive.[16] This increases the demand for these firms, but they incur adoption cost. Panel C shows the equilibrium percentage of firms δ^* that optimally automate. In the region $\delta < \delta^*$, firms have an incentive to automate to attract higher demand even if the adoption cost lowers their net profit. In the region $\delta^* < \delta < \hat{\delta}$, firms do not want to automate as the slightly higher demand does not compensate for the adoption cost κ. In the region $\hat{\delta} < \delta$, their demand is already below the demand for goods from labor-based firms. Firms are indifferent between automating and not-automating only at equilibrium δ^*, despite lower net dividends.

In a disruptive shock, all firms can become more competitive. However, without a massive change in the overall industry demand, each individual firm ends up with the same demand as its competitive advantage relative to other firms does not change, but it still incurs the adoption cost.[17] The third column in Fig. 3 shows that an automating firm charges lower price and faces higher demand than it would if it stayed labor-based at all δ and hence all firms automate with $\delta^* = 1$. This can still lead to lower net dividend.[18] Although automating is costly and doesn't provide competitive advantage relative to other firms, which also automate, each firm prefers to incur the cost instead of a more severe punishment due to lower demand. Thus, technology adoption is a costly necessity to stay competitive. Competition forces firms to undergo costly automation but its benefits are largely passed through to the consumers.

2.4. Implications for firm risk and stock returns

To show the different implications of the technology shocks on firms in each sector, Fig. 4 plots the number of automating firms in sector $s = 1$ (Panel A) and the dividends of firms in the two sectors (Panels B and C) as functions of the magnitude of the shock.

Panel A shows that the equilibrium number of automating firms increases convexly from zero for no shock to one for large A^{High}. This generalizes the equilibrium examples from previous section to a whole range of shock magnitudes with no firm automating at no shock (equilibrium 1), increasing fractions of firms automating for incremental shocks (equilibrium 2), up to all firm automating in a large shock (equilibrium 3). This relationship is weak for low levels of A^{High} but becomes stronger for larger technological improvements. I select the model parameters such that the first equilibrium type, $\delta^* = 0$, exists when $A_2 = A^{Low} <= 0.89$. The second type, $0 < \delta^* < 1$, emerges when $A_2 = A^{High}$ and $0.89 < A^{High} < 1.045$. The third type, $\delta^* = 1$, establishes if the technological change is large enough, $A_2 = A^{High} >= 1.045$.

[16] The increase in the prices of goods of automated firms across δ is due to decreasing returns to scale of the capital installation function (4). It helps depict equilibrium 2 but is not necessary for the asset pricing implications.

[17] This abstracts from the generally much smaller general-equilibrium effect at the sector level.

[18] Profits decrease compared to $t = 1$.

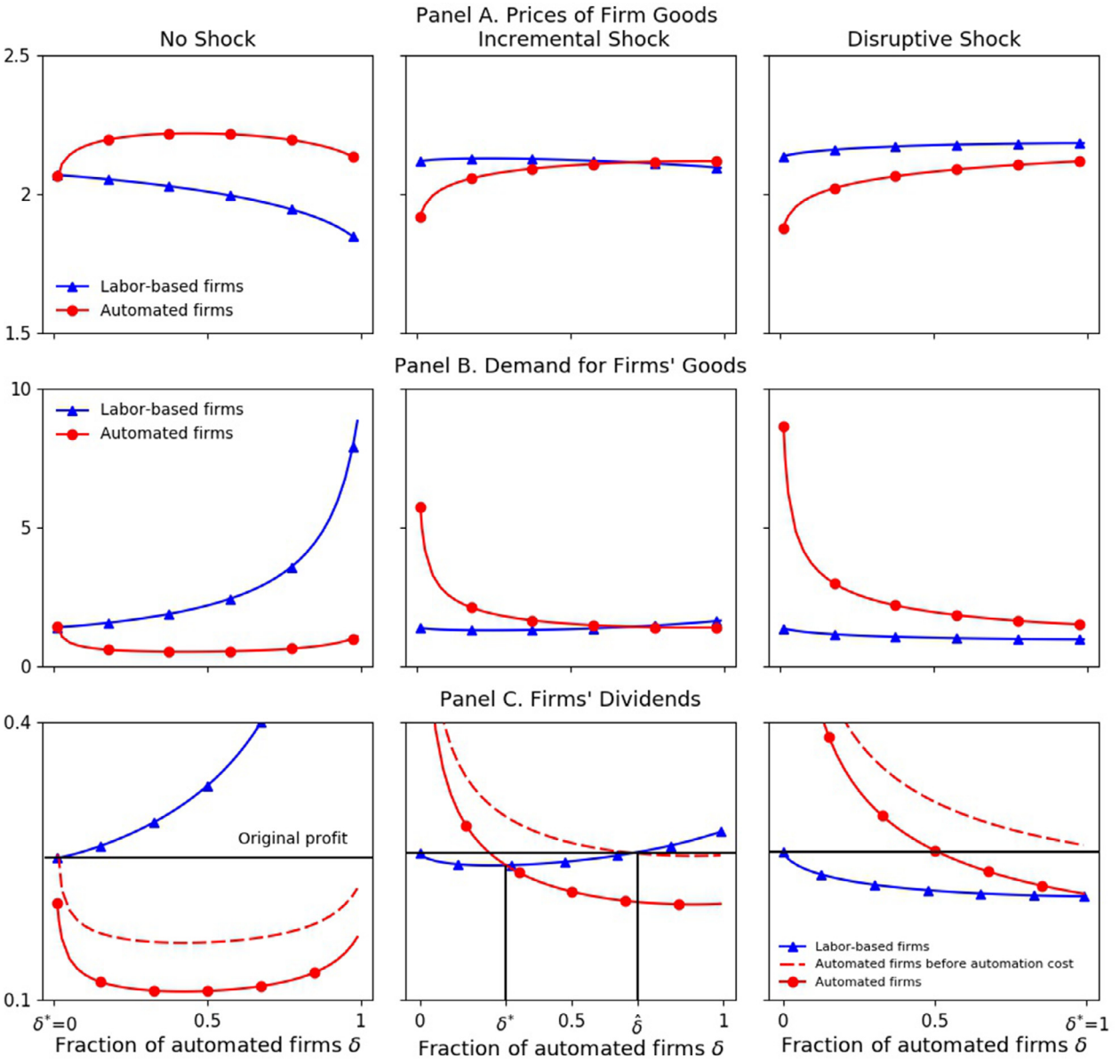


Fig. 3. Three types of sector equilibria. This figure plots the relationship between the prices of goods (Panel A), demand for goods (Panel B), and dividends (Panel C) of labor-based and automated firms within the sector $s = 1$ and the percentage of automated firms in this sector, δ, x-axis. Plots in the first column show a state of no shock. The parameter A_2 is chosen so that the good prices of each type of firm are same when no firm automates ($\delta^* = 0$). Plots in the middle column show a situation with an incremental technology shock when a percentage of firms ($0 < \delta^* < 1$) automates. Plots on the right-hand side show a situation of large disruptive technology shocks when all firms in the sector automate despite automation cost κ, ($\delta^* = 1$). The black horizontal line depicts the original dividend level. The model parameters are: $\rho = 4$, $\nu = 14.2$, $\alpha = 0.966$, $\chi = 1$, $\theta = 1.9$, $N = 1000$, $N_h = 100$, $A^{Low} = 0.87$, $A^{High} = 1.00,\ 1.045$, $\beta = 0.85$, $\gamma = 32.8$, $\epsilon = 0.32$, $p_H = 0.10$, $p_\epsilon = 0.5$, and $\kappa = 8 \times 10^{-5}$. The demand for firms' goods and firms' dividends are scaled by a factor 1000.

As the magnitude of the shock increases the number of automating firms in sector $s = 1$, the equilibrium dividends of all firms in this sector decrease (Panel B).[19] The higher number of automating firms decreases the price of the sector-aggregate good $P_{1,2}(\delta^*)$ as shown in Eq. (A.11a). Since firm's relative revenues depend on its product price relative to all firms in the sector $\left(\frac{P_{f,1,2}}{P_{1,2}(\delta^*)}\right)^{-\nu}$ with $\nu > 1$, it becomes more prohibitive to keep the labor-based production that produces goods at higher relative price. At the same time, the rents of automated firms decrease as their product prices become less competitive due to many other automated firms charging same lower price.[20] Automation

[19] In equilibrium, the dividends are identical for all firms in the sector regardless of whether the particular firm automates or not as firms are indifferent in the Nash equilibrium.

[20] This also applies to the pure-strategy equilibrium 3 where all firms automate.

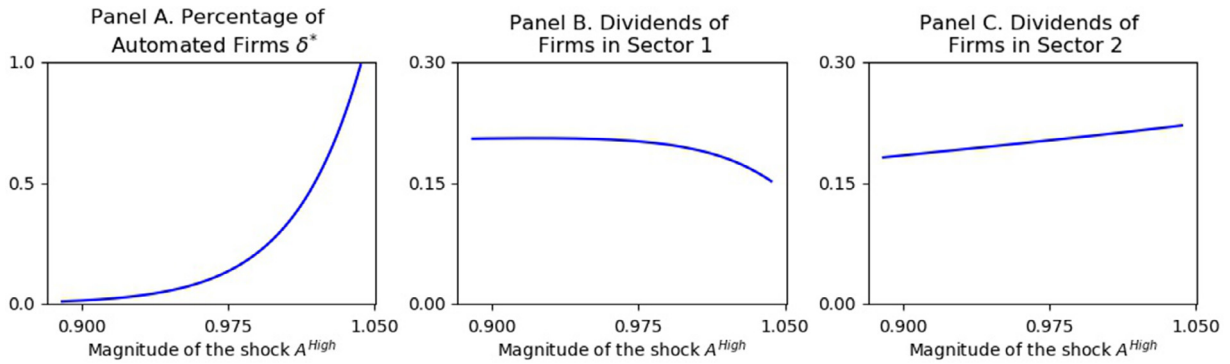


Fig. 4. Technology Shocks, Equilibrium Automation and Profits. This figure plots the equilibrium relationship between the magnitude of the technology shock A_t and percentage of firms that automate within the sector 1 (Panel A), the dividends of firms in sector 1 (Panel B) and the dividends of firms in sector 2 (Panel C). Model parameters are stated in the description of Fig. 3. Dividends are scaled by a factor 1000.

becomes a costly necessity to stay competitive.[21] The effect of the shock on firms in sector $s = 2$ is strictly positive (Panel C). Since this sector already consists of firms with capital-based production, the firms are not exposed to strategic considerations of costly adoption of technology that would decrease their dividends, and they benefit directly from lower prices of capital investment $P^I_{2,2}$ brought by a higher level of technology.

The effect of a technology shock on dividends translates to firms' risk exposure, which I plot for firms in each sector as functions of A^{High} in Panel A in Fig. 5. Firms in sector 1 have mild exposure to the shock for low values of A^{High}, but the exposure becomes strongly negative as A^{High} increases. Hence, a technology shock can decrease the value of firms in this sector resulting in a negative return on the impact of the shock.[22] Firms in sector 2, which consists entirely of capital-based firms, have positive exposure and experience positive stock return upon the occurrence of the shock. The differences in stock returns across the sectors are informative about technology shocks embodied in capital. In my empirical analysis, I show that stock return differences between firms with high and low share of displaceable labor co-move strongly with prices of capital goods, which supports the model.

To demonstrate the importance of the idiosyncratic labor income shock $\tilde{\epsilon}_h$ in the model for pricing of the aggregate technology shock A_2, Fig. 6 shows the relationship between the dispersion ϵ and the risk premium $\mathbf{E}\left[R^I\right] - R_f$ of an asset that has $\beta = 1$ exposure to the shock A_2. Households require a positive premium for this asset if the idiosyncratic labor productivity risk ϵ is low. The higher average labor productivity of spouses working in the capital production dominates due to A^{High} the idiosyncratic labor productivity risk. As ϵ increases, the idiosyncratic labor-productivity risk dominates and the return premium becomes negative. In this case, households dislike the technology shock as they may experience a severe decrease in their individual labor income. The asset becomes valuable as it outperforms during the technology shock.

For the remaining analysis I assume the premium to be negative, which is supported by the evidence presented later in this paper and in Papanikolaou (2011) and Kogan et al. (2020). Fixing the sign of the return premium then allows to derive predictions for expected returns in the cross-section of stocks. The relativity of the return premium described in Fig. 6, however, highlights that the implications of technology shocks for expected stock returns depend on the economic environment, specifically the households' ability to stay productive in new occupations. Hence, evidence from other countries can be valuable.

Panel B in Fig. 5 shows the expected stock returns of firms in each sector as functions of the magnitude of the shock A^{High}. Firms in sector $s = 1$ earn higher expected return than firms in sector $s = 2$. They have negative exposure (see Panel A) to negatively priced risk, which results in high expected returns. The positive exposure of firms in sector $s = 2$ to the same risk leads to lower expected returns.

The difference in the expected returns between firms in these two sectors increases with the magnitude of A^{High} (Panel C). This follows from two effects. First, with increasing magnitude of the shock the firm risk exposure becomes more negative in sector 1, but stays almost constant in sector 2 (Panel A). Second, the magnitude of the premium increases as a higher A^{High} increases the equilibrium number of automating firms and thereby the likelihood of displacement for households. An increasing difference in risk exposures together with an increasing magnitude of the risk premium then naturally leads to an increasing difference in expected return. Consistent with this, my empirical analysis shows that stocks with negative exposure to technology shocks have higher expected returns. I discuss further aspects of the model in Appendix C.

[21] This abstracts from inter-sectoral demand shifts, which are considerably smaller as the sector-level goods are weaker substitutes.

[22] This result is conceptually different from Lin et al. (2020). First, my technology shock is capital-embodied, which is different from theirs as discussed in their introduction. Second, they focus on capital and not labor. Third, the economic rent from adopting technology accrues mechanically to the firm in their setting as the firm is treated in isolation. In my setting, the economic rent from technology adoption that accrues to the firm is determined by general equilibrium forces.

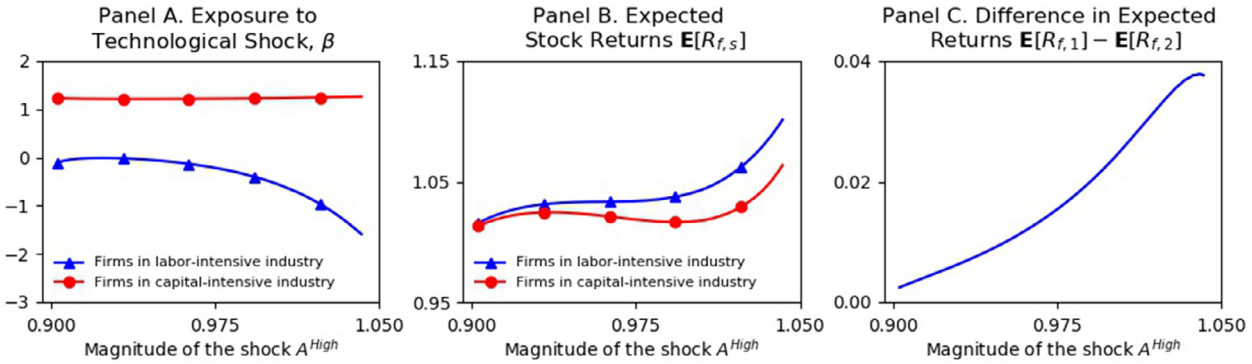


Fig. 5. Firms' exposure to technology shock and expected returns. This figure plots the relationship between the magnitude of the technology shock and firms' risk exposure (Panel A), expected stock returns (Panel B), and the differences in expected stock returns between firms in sector 1 and 2 (Panel C). Model parameters are stated in the description of Fig. 3.

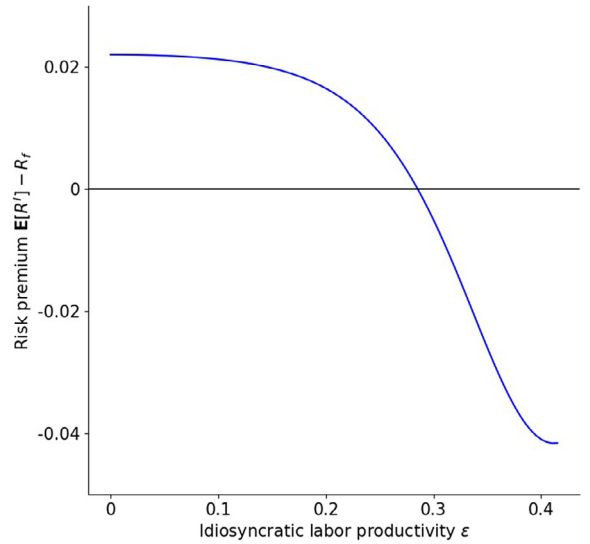


Fig. 6. Idiosyncratic labor productivity ϵ and risk premium of technology shocks. This figure plots the risk premium for technology shocks $\mathbf{E}\left[R^I\right] - R_f$ as a function of the idiosyncratic labor productivity risk ϵ. R^I is return on an asset that has $\beta = 1$ to technology shock A_2. The magnitude of the technology shock A^{High} is chosen so that all firms in sector $s = 1$ automate ($\delta^* = 1$). Model parameters are stated in the description of Fig. 3.

3. Data

3.1. Firm share of displaceable labor (automation potential)

The main input in my analysis is a measure of firms' share of displaceable labor, which I denote the **A**utomation **P**otential (AP). I use the occupational characteristics from the O*Net database, the composition of labor force from Occupational Employment Statistics (OES) and the relative importance of labor and capital to calculate the AP measure at the firm level. The AP measure for firm j at time t is:

$$AP_{j,t} = ln\left(L_{j,t}^{routine}/K_{j,t}\right), \tag{17}$$

where $L_{j,t}^{routine}$ is the number of employees in routine intensive occupations. I calculate $L_{j,t}^{routine}$ by multiplying firm's number of employees from Compustat with the percentage of jobs in routine intensive occupations in the firm's industry, which is based on detailed occupational composition from OES data and Routine Task Intensity measure based on O*Net data.

The percentage of jobs in routine intensive occupations is the employment of routine intensive occupations divided by total employment in each detailed industry.[23] Following Autor and Dorn (2013), I define routine intensive occupations as those in the top third among all occupations ranked by the Routine Task Intensity measure explained below.[24] To assess the relative importance of firm's routine labor, $L_{j,t}^{routine}$, I divide it by firm's capital, $K_{j,t}$, measured by the Compustat item "Property, Plant & Equipment (net)".[25] More details about the underlying data and robustness are in Online Appendix 3. Firms with a high AP measure correspond to firms in sector $s = 1$ in the theoretical model. These firms have a large potential to displace labor by capital. Firms with a low AP measure correspond to firms in sector $s = 2$. These firms either have a lot of capital and/or their labor is non routine and complements capital.[26]

The **R**outine **T**ask **I**ntensity measure (RTI) (originally developed by Autor and Dorn, 2013) measures the potential of replacing human workers by capital in each occupation by considering the relative importance of three groups of tasks: routine, abstract and manual. I apply this measure to more detailed and comprehensive O*NET data and provide details in Appendix B. High RTI scores indicate high

[23] I use OES occupation-industry employment statistics for detailed sic 3-digit or naics 4-digit industries.

[24] In Autor and Dorn (2013), an occupation *occ* is routine intensive if $RTI_{occ} > RTI^{66}$, where RTI^{66} denotes the 66th percentile of RTI weighted by US national occupation employment.

[25] The results are robust when ppegt is used. ppent or ppegt is preferred as it is consistently available for the full time period and the sample of firms.

[26] The definition of the AP measure is distinct from the Rshare variable in Zhang (2019). Although both measures share one similar ingredient, the routine task intensity, the measures are very different, both conceptually and empirically. My AP measure is based on the composition of production factors (capital and labor), while Rshare considers labor only. This is not a nuance, but has a substantial economic and empirical meaning as discussed in detail in Online Appendix.

Table 1
The properties of the AP measure.

	Mean	Median	St. dev.	Min	Max
Panel A. Summary statistics at the firm level					
$(-AP)$	4.546	4.305	1.393	−1.771	9.570
$ln(K/L)$	3.493	3.298	1.275	−2.507	8.169
Panel B. Summary statistics at the industry level					
$(-AP)$	4.462	4.229	1.200	1.053	8.682
$ln(K/L)$	3.407	3.243	1.055	0.214	7.069
$L^{routine}/L^{total}$	0.400	0.392	0.186	0.050	0.822
Panel C. Summary statistics at the industry level within manufacturing manufacturing					
$(-AP)$	4.136	4.016	0.865	2.045	6.654
$ln(K/L)$	3.472	3.346	0.718	1.745	5.646
$L^{routine}/L^{total}$	0.537	0.549	0.137	0.180	0.818
Panel D. Summary statistics at the industry level within transport, trade and services					
$(-AP)$	4.691	4.432	1.297	1.109	8.626
$ln(K/L)$	3.286	2.998	1.232	0.216	6.953
$L^{routine}/L^{total}$	0.281	0.266	0.138	0.050	0.683

Panel E. Decomposition of variance into within and between industry components	$(-AP)$	$ln(K/L)$	$L^{routine}/L^{total}$
Within industries	21.48	25.36	0
Between industries	78.52	74.64	100

This table reports the summary statistics of the AP measure and its main components, $\ln\left(K_{j.t}/L_{j.t}\right)$ and $L_{i.t}^{routine}/L_{i.t}^{total}$ at the firm and industry level. These components are obtained from rewriting the definition of the AP measure as: $AP = ln\left(L_{j.t}^{routine}/K_{j.t}\right) = ln\left(L_{i.t}^{routine}/L_{i.t}^{total}\right) + ln\left(L_{j.t}/K_{j.t}\right)$, where index j denotes firm and index i the industry. I drop the logarithm for $L_{i.t}^{routine}/L_{i.t}^{total}$ to allow easier interpretation of this percentage number. (−AP) denotes the negative of AP, i.e., $ln\left(K/L^{routine}\right)$, to avoid negative numbers and facilitate readability. The reported results are time-series averages of cross-sectional statistics. Panel A shows the summary statistics at the firm level and panel B at the industry level. Panels C and D report results at industry level within manufacturing sector (sic codes 2000–3999 until 2001, and naics codes 310,000–340,000 afterwards) and transport + trade + services sectors (sic codes 4000–6000 and 7000–9000 until 2001, and naics codes 410,000–520,000 and 540,000–910,000 afterwards), respectively. Panel E reports the variance decomposition of the (−)AP measure and its components into within- and between-industry variance. The numbers in panel E denote the percentage of total variance. By construction, $L_{i.i}^{routine}/L_{i.i}^{total}$ has 100% variance at industry level. Industries are defined at SIC 1987 3-digit and NAICS 2002 4-digit level.

importance of routine tasks in a given occupation. Routine tasks are defined as tasks that can be accomplished by following a precise set of rules and potentially be executed by machines programmed to follow this set of rules.[27] Occupations with high RTI score predominantly consist of routine tasks and hence have high potential to be automated by machines. Occupations with low RTI score have a low input of routine tasks but require strong input of abstract or manual tasks, such as critical thinking, active learning or negotiating and hence cannot easily be automated by machines. The routine task intensity is not the same dimension as labor skill dimension. Routine occupations are generally concentrated in the middle skill-level occupations with average labor income (Autor and Dorn, 2013).

The AP measure can vary between industries, as well as across firms within the same industry. The majority of the variation, however, is at the between-industry level. Table 1 reports the summary statistics and cross-sectional variance decomposition of the AP measure into within- and between-industry variation. Panel A shows that there is a considerable variation in the share of displaceable labor measured by the AP measure at the firm level across firms in all industries, and Panel B shows that similar variation is present also when firm-level observations are aggregated at the industry level, i.e., variation between industries.

Panels C (manufacturing) and D (transport, trade and services) show the AP measure of industries within two broad sectors. The average level of the AP measure is not remarkably different between those two sectors, but both show significant industry variation within the sectors. This reassures first that my empirical results that follow are not driven purely by broad sectoral variations in this measure. Secondly, I use industry variation within those broad sectors to provide a robustness check to my main results based on variation in AP at the firm level. (See Online Appendix 5.5.5.)

Panel E decomposes the variance of AP into within-industry and between-industry variance. The majority of

[27] Autor et al. (2003) define routine tasks as: "In our usage, a task is 'routine' if it can be accomplished by machines following explicit programmed rules. Many manual tasks that workers used to perform, such as monitoring the temperature of a steel finishing line or moving a windshield into place on an assembly line, fit this description. Because these tasks require methodical repetition of an unwavering procedure, they can be exhaustively specified with programmed instructions and performed by machines."

variation, 78%, is attributable to between-industry variation. This fits nicely with my model, where ex ante identical firms within an industry have similar costs of capital and return properties due to the labor substitutability characteristics of the industry. Of course empirically, firms within an industry are not exactly identical, and the smaller amount of within industry variation can be attributed to aspects not explicitly captured by my model, such as variation in timing of labor substitution and general unmodeled heterogeneity.[28] One might suspect that the high level of between-industry variation is somewhat mechanical or due to the data limitation that one component of the AP measure is defined only at the industry level. Panel E shows that the part of the AP measure that is defined at the firm level, $ln\left(\frac{L_{j,t}}{K_{j,t}}\right)$, still has nearly 75% of its variation attributable to between-industry variation. Hence, the focus of my model on labor substitutability at the industry level is appropriate, but my primary empirical work does allow for firm level variation within industries, and in robustness checks I show that my main results also hold in purely industry-level analysis.

As with any empirical analysis, one might be concerned that my AP measure correlates with other important characteristics, such as industry elasticity of demand. My analysis endeavors to address these concerns through robustness analysis by carrying out the analysis at firm level, industry level and for industries within the broad sectors.

3.2. Financial data

I use monthly stock return data from CRSP for common stocks (SHRCD=10, 11) listed on NYSE, NASDAQ, and AMEX from 1970 to 2015. To calculate the AP measure, I require the firms to have underlying data for the number of employees and total net capital in the Standard and Poor's Compustat database. Hou et al. (2017) find that a large number of previously documented cross-sectional return anomalies are affected by micro-cap stocks. To address this concern, I exclude micro-cap stocks, which Hou et al. (2017) defines as stocks with the market equity below the 20th percentile of NYSE listed stocks. Robustness exercises with delisting return values as suggested by Shumway (1997) and in a sample of S&P500 stocks provide similar results.[29]

3.3. Technology shocks embodied in capital

I measure the technology shocks embodied in capital A_t by the changes in quality-adjusted relative prices of capital goods. The formal theoretical validity of this measure has been derived in previous literature (Greenwood et al., 1997; Cummins and Violante, 2002; Hornstein and Krusell, 1996), and the measure has been used in a number of studies (Greenwood et al., 1997; 2000; Fisher, 2006). The intuition behind the theoretical foundation is that investment-specific technology shocks allow for production of new capital goods, such as machines, software or equipment, at lower cost or with higher quality. Hence the changes in the quality-adjusted prices of capital goods relative to aggregate prices are informative about the technological progress. As in previous literature, I construct the measure of capital-embodied technology shocks by subtracting the log changes in the quality-adjusted prices of capital goods from the log changes in the aggregate price level and denote it I-shock measure. An increase in the I-shock indicates a positive technology shock and is associated with higher quality and/or lower prices of capital goods.[30]

The underlying price indexes are from the BEA. I measure the aggregate price level by the price index of the personal consumption expenditures for nondurable goods. The quality-adjusted prices of capital goods are based on the price index for private fixed investment in nonresidential equipment. I use annual frequency for both time-series and calculate the I-shock measure from 1970 to 2015. To account for the changes in quality of capital goods such as computers and peripherals, the BEA introduced hedonic-based quality adjustments in the underlying price indexes since 1980s.[31] I further account for possible quality changes by using the quality adjustment from Cummins and Violante (2002) and provide details in Online Appendix 4. The I-shock measure exhibits patterns and properties in line with previous literature (Fisher, 2006), e.g., positive mean indicating a secular decrease in prices and increase in quality of capital goods. In Online Appendix I also show robust result with an alternative measure of capital-embodied technology shocks based on relative productivity shocks of automation capital-goods producing industries TFP^{aut}. This measure is conceptually related to the I-shock and both correlate strongly.

The dashed blue line in Fig. 1 plots the normalized time-series of the I-shock measure from 1970 to 2015. I normalize the I-shock to mean zero and standard deviation of one to facilitate comparison with a factor-mimicking portfolio described later. Since the original I-shock measure has a significantly positive mean of 4.0 percent, a zero value of the normalized measure still indicates a positive technological progress. The most prominent and pervasive technology shock during this period was from 1997 to 2001, when the normalized I-shock recorded a cumulative increase of 5.71 standard deviations. This peak relates to a large productivity shock in a single manufacturing industry, the electronic computer manufacturing industry (NAICS 334111), which is a major producer of automation-relevant equipment, and it was accompanied with an unprecedented increase in quantity and decrease in prices of the industry's shipments. As such, it is consistent with

[28] The model, however, allows a degree of within industry variation as an endogenous outcome in the mixed-strategy equilibrium.

[29] See Online Appendix. Previous version of this paper used a set of filters based on size, trading volume, price, data history and minimum values of capital and number of employees. The results were similar.

[30] In robustness exercise, I also extract the innovations in the I-shock measure ϵ_t^I from AR1 model $Ishock_t = \alpha + \rho \times Ishock_{t-1} + \epsilon_t^I$. The results based on ϵ_t^I are practically same or even stronger.

[31] Wasshausen et al. (2006) provide an overview of the use of hedonic methods by the BEA to measure real GDP; Fox and McCully (2016) provide information about the price indexes for all types of equipment and discusses the quality adjustments employed by BEA.

Table 2
Technology shocks and income growth.

Panel A. Impact of technology shock on average personal income						
	Growth in income per capital, BEA			Average income growth, Guvenen et al. (2014)		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
Constant	0.052***	0.11***	0.087***	0.017***	0.024***	0.03***
	(0.011)	(0.02)	(0.015)	(0.005)	(0.005)	(0.007)
Ishock	−0.117	−0.33	−0.363**	−0.106	−0.206*	−0.284**
	(0.135)	(0.245)	(0.163)	(0.149)	(0.106)	(0.113)
TFP	0.376	0.336	0.212	0.9***	0.584***	0.414***
	(0.447)	(0.763)	(0.514)	(0.295)	(0.191)	(0.136)
R^2	4.49	5.56	12.59	18.63	13.29	14.5
Panel B. Impact of technology shock on distribution of income growth						
	Standard deviation of income growth			Skewness of income growth		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
Constant	−0.008**	−0.015***	−0.01**	0.165*	0.283***	0.116**
	(0.004)	(0.005)	(0.004)	(0.092)	(0.099)	(0.055)
Ishock	0.102	0.243**	0.149	−4.473**	−6.28***	−2.631**
	(0.099)	(0.111)	(0.095)	(1.835)	(1.659)	(1.084)
TFP	0.023	−0.07	−0.055	6.267**	1.635	0.194
	(0.161)	(0.15)	(0.103)	(2.513)	(2.724)	(1.635)
R^2	5.13	14.29	14.64	33.81	30.31	19.38

This table reports the results of regressing growth of income per capita, cross-sectional average of income growth and change in moments of cross-sectional income growth distribution on the I-shock measure and TFP shock. The regression is specified in (18). The dependent variables $y_{t+k} - y_{t+k-1}$ in Panel A are the log growth rate in average income per capita and cross-sectional average of annual personal income growth rates and in Panel B the change in the standard deviation and skewness of cross-sectional personal income growth rates as indicated in headings. TFP is the change in aggregate productivity between $t-1$ and t. The regressions are estimated at annual frequency. The time period in the first three columns of panel A is from 1975 to 2015 and from 1978 to 2010 in the remaining part. In this and subsequent tables, ***/**/* indicates significance at the 1%/5%/10% level. Source: Income per capita: U.S. Bureau of Economic Analysis through St. Louis FED (FRED); Moments of income growth distribution: Guvenen et al. (2014).

adoption of IT in so called IT revolution studied in, e.g., Pástor and Veronesi (2009). I link also other major I-shocks to a differential productivity growth of a small number of capital-goods, particularly automation capital, producing industries, some of which received attention in previous literature (Hobijn and Jovanovic, 2001; Greenwood and Yorukoglu, 1997, 1974) in Online Appendix Table IA.15.

3.4. I-shock as an income state variable

Recent studies, e.g., Gârleanu et al. (2012); Kogan et al. (2018) show that technology shocks have important negative effects on households' income. Knesl (2018) links capital-embodied technology shocks to time-varying job-displacement and labor-income risk as lower prices of capital goods allow substituting capital for labor in occupations that have the potential to be automated. Thus, technology shocks embodied in capital are an important state variable indicating the household income risk, which I illustrate with simple regressions below.

Panel A in Table 2 reports the results of regressing contemporaneous and future log growth in personal income on the I-shock and the aggregate productivity shock (TFP). Specifically, I estimate the regression

$$\frac{1}{K+1}\sum_{k=0}^{K} y_{t+k} - y_{t+k-1} = \alpha + \gamma_{Ishock} \times Ishock_t + \gamma_{TFP} \times TFP_t + \epsilon_{t+k}, \quad (18)$$

where $y_{t+k} - y_{t+k-1}$ is the log growth rate in average income per capita from the BEA or cross-sectional average of personal income growth from Guvenen et al. (2014).[32] $Ishock_t$ is the I-shock measure representing the change from $t-1$ to t. The TFP_t is the change in the aggregate productivity over the same time period. I estimate the regression at annual frequency for time horizons $K = 0$, 1, and 2. The first three columns show that a positive technology shock embodied in capital (I-shock) is associated with a slightly lower growth in average income per capita, and the effect becomes significant at the horizon of two years. The next three columns provide a similar results for the average of cross-sectional personal income growth in the data from Guvenen et al. (2014).

Although these results suggest a somewhat adverse effect of technology shocks on average income growth, looking only at the aggregate or average income growth can hide important effect of technology shocks on *individual* personal income growth. For this, higher moments, i.e., variance and skewness of cross-sectional distribution of individual income growth, are more informative. I focus on them as dependent variables in Panel B using the data from Guvenen et al. (2014). The first three columns show that the standard deviation increases only slightly following a positive I-shock. However, a positive technol-

[32] I use nominal personal income to avoid a potential mechanical effect of deflating as the I-shock measure contains changes in prices of consumption goods in its numerator.

ogy shock has a strongly negative effect on the skewness of individual income growth as shown in the last three columns. As a positive I-shock significantly increases the left skewness of the income growth distribution, individuals are more likely to experience large drops in personal income, e.g., job loss, in years following such a shock.[33]

This result supports the assumption of the state-dependent idiosyncratic labor productivity risk in my model. Higher moments of the cross-sectional distribution of individual income growth play a central role in pricing assets in incomplete markets when agents face uninsurable income risk. In the model of Constantinides and Duffie (1996), the second moment of the cross-sectional distribution of individual income enters the stochastic discount factor. Constantinides and Ghosh (2017) show that the third central moment of individual income growth drives asset prices and risk-free rate. Schmidt (2016) provides evidence that the idiosyncratic tail risk of income growth is state-dependent and predicts stock returns.

4. Technology shocks and displaceable labor

4.1. Co-movement

I sort stocks into five portfolios based on their share of displaceable labor (AP) to examine the time-series and cross-sectional properties of stock returns associated with firms' automation potential. The first portfolio consists of stocks with the highest AP. These firms also have high labor intensity and a high percentage of employees in routine occupations. The average AP measure then decreases from −3.18 in the first portfolio to −7.2 in the fifth portfolio. The portfolios are rebalanced annually at the end of June and value weighted.[34]

Fig. 1 plots the I-shock measure and the annual stock return difference between firms with low and high displaceable labor share, i.e., long-short portfolio with a long (short) position in the bottom (top) quintile of firms ranked by the AP measure. I denote this portfolio the KML portfolio (**K**apital **M**inus **L**abor).[35] These two time-series co-move very strongly and overlap in all spikes. The correlation coefficient is slightly below 50% for the basic I-shock measure, slightly above 50% when innovations in I-shock from first-order autoregressive model are used, and reaches 60% percent for KML portfolio constructed from S&P500 stocks (Panel A in Table 3).[36]

This strong co-movement is a robust feature of the data and it is present across various samples of firms. It holds when I exclude firms producing capital goods from the sample, and it is independently present among both, manufacturing and non-manufacturing firms.[37] This result indicates a strong connection between a macroeconomic variable measuring changes in quality-adjusted prices of capital goods and the dynamics of stock returns. These findings support the prediction of the theoretical model that technology shocks embodied in capital lead to different stock price reactions between firms with low and high share of displaceable labor. The strong co-movement of the KML portfolio and the I-shock measure over the last 45 years shows that the stock return differences between these two types of firms are informative about capital-embodied technology shocks as implied by the model.[38]

I first examine whether the co-movement of the KML portfolio with the I-shock is driven by ranking individual firms relative to industry peers or by ranking whole industries across the economy. Panel B in Table 3 reports the correlation coefficients between the I-shock and long-short (KML) portfolios constructed on either within- or between-industry variation in the AP measure. The correlation is strong, 0.44-0.49, for KML portfolios based on the between-industry variation, i.e, ranking whole industries across the economy. It is weak for long-short portfolios based on the within-industry variation, i.e., firms ranked relative to industry peers. This aligns with the dominance of the between-industry variation in the AP

Table 3
Correlation between the I-shock measure and the long-short (KML) portfolios based on the between- and within-industry automation potential.

Panel A. Correlation coefficients		
	KML (NYSE 20)	KML (S&P 500)
Ishock	0.467	0.55
Ishock AR1 innovation	0.527	0.6

Panel B. Within- vs. between-industry correlation coefficients				
	SIC 4	SIC 3	NAICS 6	NAICS 5
Between industries	0.442	0.445	0.476	0.487
Within industries	0.115	0.123	0.223	0.189

Panel A shows correlation coefficients between the KML portfolios constructed from stocks above NYSE 20*th* percentile and S&P500 as indicated in columns and Ishock measure and AR1 innovations in Ishock measure (i.e., surprise shocks) as indicated in rows. Panel B reports the correlation coefficients between the I-shock measure and the long-short portfolio (KML) constructed by the AP measure based on within or between industry variations. The long-short portfolios in the 'Between' row are constructed by ranking industries by the industry-level average share of AP. The long (short) position consists of firms in industries in the bottom (top) quintile ranked by the average AP measure. The portfolios in the 'Within' row are constructed by ranking individual firms by firms' deviation from the industry average share of displaceable labor. The long (short) position consists of firms in the bottom (top) quintile ranked deviation from industry's average AP. Industries are defined at SIC 4-digit and 3-digit, and NAICS 6-digit and 5-digit level as indicated.

[33] Online Appendix Table IA.17 shows robust results with an alternative specification of the variables.

[34] Online Appendix Table IA.18 provides summary of the portfolio characteristics.

[35] The intentional misspelling of the word "capital" is motivated by the common use of "K" to denote capital in theoretical models and also by avoiding confusion with "CML" (capital market line).

[36] Papanikolaou (2011) uses AR1 innovations in prices of capital goods as a proxy for capital-embodied technology shocks.

[37] See Figure IA.3. The result in the sample without capital-goods-producing industries demonstrates that the identification of the co-movement of the KML portfolio with the I-shock measure is different from the identification in Papanikolaou (2011), which utilizes the return differences between capital-goods-producing and other industries. Hence, my approach complements the seminal contribution of Papanikolaou (2011).

[38] The KML portfolio also co-moves strongly with the alternative measures of capital-embodied shocks *gIMC* used in Garlappi and Song (2016) and also TFP^{aut} (see Figures IA.5 and IA.4 in Online Appendix).

Table 4
Exposure of portfolio returns to technology shocks (I-shocks).

	High AP	2	3	4	Low AP	Low-high AP (KML)
Panel A. Exposure to I-shock measure						
Ishock	−2.843***	−2.303**	−2.11***	−1.768**	−1.013	1.83***
	(0.912)	(0.869)	(0.77)	(0.72)	(0.758)	(0.411)
R^2	24.56%	19.1%	14.88%	11.87%	4.23%	21.85%
Panel B. Exposure to I-shock measure and market return						
Ishock	−1.21***	−0.651***	−0.253	−0.001	0.684**	1.894***
	(0.433)	(0.218)	(0.303)	(0.148)	(0.259)	(0.345)
Market	0.84***	0.85***	0.956***	0.909***	0.873***	0.033
	(0.105)	(0.081)	(0.023)	(0.024)	(0.045)	(0.121)
R^2	80.77%	87.25%	94.83%	94.02%	86.54%	22.04%
Panel C. Exposure to I-shock measure, SMB and HML factors						
Ishock	−0.842***	−0.43**	−0.379	−0.108	0.675**	1.516***
	(0.234)	(0.161)	(0.261)	(0.148)	(0.285)	(0.263)
Market	0.872***	0.901***	0.914***	0.923***	0.91***	0.038
	(0.036)	(0.042)	(0.024)	(0.023)	(0.032)	(0.04)
SMB	0.326***	0.085	−0.005	−0.178***	−0.141*	−0.467***
	(0.082)	(0.076)	(0.069)	(0.051)	(0.083)	(0.136)
HML	0.194	0.203*	−0.149***	0.008	0.097	−0.097
	(0.172)	(0.117)	(0.041)	(0.04)	(0.079)	(0.231)
R^2	87.62%	90.23%	96.02%	95.55%	87.95%	42.65%
Panel D. Negative of automation potential (−AP)						
(−*AP*)	3.185	3.857	4.443	5.216	7.201	

This table reports the results from regressing portfolio annual excess returns on a constant, the I-shock measure and return factors. Regressions in Panel A include a constant and the I-shock measure. The aggregate market return is added to the regressions in Panel B, and the size (SMB) and value (HML) factors in Panel C. Panel D shows the average (−AP) for each portfolios. Stocks are assigned to one of five portfolios based on the AP measure. Portfolios are value-weighted and rebalanced annually at the end of June. The sample period is from 1970 to 2015. Newey and West (1987) standard errors are in parentheses.

discussed above (Panel C in Table 1). Both pieces of evidence underline the role of displaceable labor share as an industry characteristic.[39]

I next examine which position of the long-short KML portfolio is the main source of its co-movement with the I-shock measure and how the exposure to technology shocks (i.e., β^{Ishock}) varies across the five AP-sorted portfolios. Panel A in Table 4 reports the results from regressing annual portfolio returns on a constant and the I-shock measure. The first portfolio, consisting of stocks with the highest share of displaceable labor, has the strongest and most negative exposure to technology shocks. The coefficients are negative for all five portfolios. They increase monotonically across all portfolios from −2.843 for the first portfolio to −1.013 for the fifth portfolio and are significant for the first four portfolios. This shows that the strong co-movement of the KML portfolio with the I-shock measure is generated by stocks with high share of displaceable labor (AP). These stocks react *negatively* to technology shocks. The KML portfolio, i.e., Low-High AP, then exhibits positive and significant exposure to technology shocks of 1.83.

Panel B repeats the analysis controlling for the aggregate market return. The pattern remains monotonic across the portfolios. A notable difference is an upward shift of the I-shock coefficients so that the fifth portfolio has positive and significant exposure, while the first two portfolios still keep significantly negative exposure. The KML portfolio has positive exposure of a similar magnitude, which is driven largely again by the short position (high AP firms) contributing 1.21 out of 1.894. The exposure of the KML portfolio to market is practically zero. This is an important distinction from Zhang (2019). While Zhang's main observation is that Rshare sorts are related to β^{market}, the AP-sorts have a clear relationship to technology shocks β^{Ishock} and are unrelated to the market risk exposure β^{market}. The results are similar when the size (SMB) and value (HML) factors are included (Panel C).

Online Appendix 5.5.4 provides additional results and robustness. For example, the results are similar with the alternative measure and also for industry portfolios sorted on industry AP within broad sectors. The KML portfolio has a meaningful exposure to the IMC portfolio (Papanikolaou, 2011), but the loadings seems to arise from the long rather than the short position.

The results align with the predictions of the theoretical model. Technology shocks embodied in capital have strongly negative impact on firms with high share of displaceable labor. These firms are generally labor-intensive with relatively low capital but high use of labor that can be automated. Firms with low share of displaceable labor have slightly positive exposure. Thus, the price dynamics of stocks with displaceable labor is informative about capital-embodied technology shocks and, consistent with the model, the long-short KML portfolio appears as an empirically capable measure of these technology shocks.

[39] I use sic and naics industrial classifications that are considerably more granular than Fama–French industries. The exposure to technology shocks may change over time as the AP changes over time.

Table 5
Properties of portfolios sorted on β^{KML}.

	Low β^{KML}	2	3	4	High β^{KML}
Panel A. Exposure to I-shock, postranking betas					
Ishock	−2.551***	−2.162***	−1.981***	−1.491**	−0.164
	(0.793)	(0.617)	(0.606)	(0.626)	(0.901)
R^2	22.12%	21.46%	16.22%	10.62%	0.09%
Panel B. Additional properties					
(−)AP	4.236	4.326	4.509	4.869	5.587
BM	0.542	0.580	0.607	0.633	0.568
β^{market}	1.246	1.039	0.953	0.934	1.202
CF	0.096	0.095	0.091	0.085	0.088
Lev	0.316	0.338	0.363	0.387	0.350
PCM	0.331	0.342	0.355	0.353	0.353
Profitability	0.275	0.282	0.283	0.271	0.245
Size	6.285	6.600	6.730	6.807	6.817
Turnover	0.120	0.087	0.077	0.079	0.116

This table reports the results from regressing portfolio annual excess returns on a constant and the I-shock measure (Panel A) and additional characteristics across the stocks in each portfolio (Panel B). Stocks are assigned to one of five portfolios based on their exposure to the KML portfolio, β_i^{KML}. Portfolios are rebalanced annually at the end of June and value-weighted. Newey and West (1987) standard errors are in parentheses. (−)AP is the negative of firm's automation potential measured by $(-1) \times \ln\left(L^{routine}/K\right)$, BM is the book-to-market ratio, β^{market} is the regression coefficient of market excess return from rolling time-series regressions of firm excess return onto market excess return and a constant, CF denotes cash flow, Lev financial leverage, and PCM the price-to-cost margin. Profitability is the ratio of sales minus cost of goods sold, interest expenses, and selling, general, and administrative expenses to book equity. Size is the natural logarithm of the market capitalization in thousands, and Turnover is the fraction of shares traded to the total shares outstanding. The numbers are time-series averages of the portfolio averages from each year. The sample period is from 1975 to 2015.

4.2. Firms' exposure to technology shocks

The previous section shows that consistent with the model the stock return differences between firms with low and high AP measure (the KML portfolio) strongly correlate with the I-shock time-series. Using the KML portfolio as a proxy for I-shock, I estimate firm exposure to technology shocks directly from stock returns. Specifically, for each firm I estimate the exposure to technology shock β_i^{KML} from a rolling regression:

$$R_{i,t}^e = \alpha_i + \beta_i^{KML} R_{KML,t} + \epsilon_{i,t}, \tag{19}$$

where $R_{i,t}^e$ denotes firm $i's$ monthly excess return and $R_{KML,t}$ is the monthly return on the KML portfolio. I also control for aggregate stock market return, but including market return as a control does not matter substantially for subsequent results.[40] I estimate this regression for every stock in the sample each year at the end of June using monthly returns over the last 60 months, which allows β_i^{KML} vary over time.[41]

As shown above, the I-shock measure is a state variable indicating the labor-income and job-displacement risk, especially the risk of large adverse idiosyncratic events such as job loss that are pronounced in negative skewness of income growth distribution. Thus, the β_i^{KML} measures stock's exposure to the labor-income risk directly from the covariances of the returns with the state variable. Although AP and β^{KML} are related and correlate with each other, β_i^{KML} captures directly stock $i's$ co-movement with a state variable that is relevant for investors marginal utility.

I next focus on the properties of portfolios sorted by β^{KML}. The portfolios are constructed and rebalanced annually at the end of June and value weighted. First, I estimate the post-ranking exposure of each portfolio to the I-shock by regressing their annual returns on a constant and the I-shock measure (Panel A). It is reassuring that the β^{KML}-sorted portfolios exhibit a clear pattern similar to Table 4. The exposures are increasing monotonically from strongly negative −2.551 (significant at 1%) for the Low-β^{KML} portfolio to mildly negative and insignificant −0.164 for the High-β^{KML} portfolio. This demonstrates that β^{KML} successfully estimates exposure to the underlying state variable, the I-shock measure. Firm exposure to the KML portfolio predicts the exposure to the I-shock at horizon of at least one year.

Panel B shows additional properties. The share of displaceable labor (AP) is the main characteristic standing out with a clear pattern. It monotonically increases across the portfolios, which is consistent with low-automation-potential firms having weaker exposure to technology shocks. Other characteristics are flat across the portfolios or do not exhibit a clear pattern, with size being a mild exception and somewhat increasing.

[40] From econometric perspective, it is sound to include market as a control variable even if the theoretical model abstracts from factor-neutral market risk. Previous version of this paper based on β^{KML} estimated without market as a control had similar overall results.

[41] I require the stock to have at least 30 observations in the last 60 months.

Table 6
Mean portfolio returns and alphas of portfolios sorted on β^{KML}.

	Low β^{KML}	2	3	4	High β^{KML}	High-low β^{KML}
Panel A. Value-weighted portfolio excess return						
Excess return	11.97***	10.45***	7.74***	7.04***	5.87**	−6.09**
	(2.77)	(2.53)	(2.48)	(2.38)	(2.97)	(2.5)
Panel B. Equally-weighted portfolio excess return						
Excess return	12.12***	11.52***	10.04***	9.42***	6.81**	−5.32**
	(3.07)	(2.63)	(2.48)	(2.43)	(3.24)	(2.2)
Panel C. CAPM						
Alpha	3.438**	2.627*	0.364	−0.151	−2.539	−5.977**
	(1.403)	(1.365)	(0.955)	(0.649)	(1.672)	(2.848)
Market	1.061***	0.973***	0.918***	0.895***	1.047***	−0.014
	(0.062)	(0.063)	(0.045)	(0.024)	(0.086)	(0.141)
R^2	81.82%	84.22%	88.1%	91.49%	75.6%	0.02%
Panel D. Three-factor model of Fama and French (1993)						
Alpha	2.224**	1.107	−0.442	−0.5	−0.955	−3.179*
	(1.115)	(0.842)	(0.772)	(0.538)	(1.15)	(1.912)
Market	1.061***	1.033***	0.971***	0.934***	1.013***	−0.049
	(0.049)	(0.035)	(0.02)	(0.021)	(0.057)	(0.095)
SMB	0.173*	−0.051	−0.124***	−0.128***	−0.074	−0.248
	(0.099)	(0.063)	(0.039)	(0.026)	(0.063)	(0.155)
HML	0.187*	0.318***	0.199***	0.109***	−0.291**	−0.478**
	(0.111)	(0.096)	(0.071)	(0.037)	(0.138)	(0.239)
R^2	83.42%	88.03%	90.78%	93.07%	77.84%	9.88%

This table reports the time-series averages of value-weighted portfolio excess returns (Panel A), equally-weighted portfolio excess returns (Panel B), results of regressing monthly value-weighted portfolio excess returns on a constant and market excess return (Panel C) and results from similar regressions with additional size (SMB) and value (HML) factors from Fama and French (1993) in Panel D. Newey and West (1987) standard errors are reported in parentheses. Stocks are assigned to one of five portfolios based on their exposure to the KML portfolio β^{KML}. Portfolios are rebalanced annually at the end of June. The average excess returns in Panel A and B, Alpha estimates in Panel C and D and their standard errors are annualized. The sample period is from 1975 to 2015.

In the next section, I directly use the estimated β^{KML} to test the asset pricing implications. Whether to use covariances (β^{KML}) or firm characteristic (AP) in formal asset pricing tests deserves some discussion. In general, covariances are conceptually the correct measure for testing asset pricing implications from a theoretical point of view, although firm characteristics are, in some instances, preferred empirically as measures of stock's exposure to underlying state variables. This is based on the expectation that characteristics are measured precisely, but betas are only noisy estimates. This argument is less applicable in the case of AP and β^{KML} for two reasons. First, despite the best possible effort to precisely measure firm's automation potential, AP, it contains noise. The classification of displaceable labor in the numerator (RTI measure) is meaningful and consistent with other literature, but it is only an imprecise identification of replaceable occupations as in other papers. Autor (2013) points out some of the limitation of previous RTI measures. Although my RTI measure is more detailed than previous RTI measures, it still contains noise. Firm's capital in the denominator of AP may also be influenced by accounting elements such as, e.g., imprecise depreciation or capitalization of leases. Second reason is conceptual. In my model, firm's exposure to technology shock is *not* purely a firm characteristic, but it arises as an industry equilibrium *outcome*. Although AP seems to capture the exposure at least partially, it is only an approximation. Creating a unique and precise empirical *one-to-one* mapping between AP and firm's exposure would require conditioning on all variables affecting the equilibrium. For these reasons, AP appears conceptually and empirically less precise measure of firm's exposure to the state variable than the return covariance with the state variable itself (β^{KML}). Hence, I prioritize β^{KML} as a more direct and practical measure of firm's exposure. I report results based on the AP measure in Online Appendix.

5. Return premium and additional results

I document that a stock's expected return is related to its exposure to technology shocks β^{KML} and estimate the return premium from the cross-section of stocks. Further, I show that the exposure implies differential employment and investment behavior and financial underperformance consistent with the mechanism in the model.

5.1. Return premium

To examine whether differences in stocks' exposure to technology shocks are associated with differences in their average returns, I sort stocks into five value-weighted (unless stated otherwise) portfolios by their β^{KML} as described in the previous section. The resulting portfolios time-series are from 1975 to 2015.[42]

Panel A in Table 6 reports the average annualized portfolio excess returns. The first portfolio (Low β^{KML}) has the

[42] The first five years 1970–1975 are used to estimate the β^{KML} for portfolios formed in June 1975.

Table 7
Fama–MacBeth regressions of annual stock returns on β^{KML} and firm characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{KML}	−3.617**	−3.077**	−3.639***	−3.716***	−3.316**	−3.564***	−3.74***	−3.27**	−3.473**	−3.157***
	(1.571)	(1.644)	(1.402)	(1.478)	(1.374)	(1.456)	(1.335)	(1.561)	(1.66)	(1.267)
β^{Market}		0.488								1.089
		(2.208)								(1.747)
BM			3.195***							6.239***
			(1.228)							(2.098)
Lev				1.852**						−2.996**
				(0.834)						(1.303)
CF					14.459**					−6.256
					(6.013)					(6.494)
PCM						2.905				4.491*
						(2.656)				(2.819)
Size							0.001			0.002
							(0.002)			(0.002)
Prof								13.77***		14.412***
								(2.535)		(3.658)
Turnover									7.898	2.214
									(31.687)	(15.487)

This table reports results of Fama–MacBeth regressions of individual annual stock returns on β^{KML} and other variables indicated in individual rows as specified in Eq. (20). β^{KML} is the firm i's exposure to technology shock in year t estimated from a rolling window of last 60 monthly returns. Other variables are defined in the notes of Table 5. The reported coefficients are $\bar{\lambda}^{\beta^{KML}}$ and $\bar{\lambda}^{n}$ calculated as time-series averages of the estimated yearly $\lambda_t^{\beta^{KML}}$ and λ_t^n, respectively. Standard errors with Newey and West (1987) correction are in parentheses. The sample period is from 1975 to 2015.

highest average excess return of 11.97%. This portfolio consists of stocks with the most negative β^{KML}. The average excess returns decrease monotonically across the portfolios. The long-short High-Low β^{KML} portfolio earns a significant negative premium of −6.09% per year. The results are very similar for equally-weighted portfolio returns reported in panel B.

Panel C shows that the return differences are also not explained by market return. The estimated alphas exhibit a similar pattern as average excess returns, decrease monotonically, and the High-Low β^{KML} portfolio earns significant negative alpha of −5.977%.[43] Regressions in panel D control also for size (SMB) and value (HML) factors. Although the estimated alphas are somewhat smaller in their magnitude compared to Panel C, they are still sizable, have similar pattern, and the long-short portfolio generates a meaningful alpha of ca. 3.2%.

I next use Fama–MacBeth (Fama and MacBeth, 1973) regressions with firms' annual stock returns to differentiate the return premium associated with β^{KML} from other well-known cross-sectional return predictors. Specifically each year t, I run Fama–MacBeth regressions at the firm level:

$$R_{i,t+1} = \alpha_t + \lambda_{t+1}^{\beta^{KML}} \times \beta_{i,t}^{KML} + \sum_n \lambda_{t+1}^{n} \times X_{i,n,t-1} + \epsilon_{i,t+1}, \quad (20)$$

where $R_{i,t+1}$ is firm i's annual stock return from July of year t to June of year $t+1$, $\beta_{i,t}^{KML}$ is a firm's exposure to technology shock at the end of June of year t, and $X_{i,n,t-1}$ are other firm-level predictors at the end of year $t-1$.[44] The estimates $\bar{\lambda}^{\beta^{KML}}$ and $\bar{\lambda}^{n}$ are calculated as averages of the yearly estimates of $\lambda_t^{\beta^{KML}}$ and λ_t^n.

Table 7 presents the results. The specification in column 1 includes only a constant and β^{KML}. The estimated coefficient is negative and strongly significant. The coefficient implies an average return differential of −5.557% per year between firms with high and low β^{KML}.[45] Columns 2–9 show results for regressions with β^{KML} and one of the predictors $X_{i,n,t-1}$ at a time. Each of these predictors has only a negligible impact on the estimated coefficient of β^{KML}. The coefficient stays negative and significant across the specifications. The implied return difference between firms with high and low β^{KML} ranges from −4.72% to −5.75% per year. The last column controls jointly for all variables $X_{i,n,t-1}$. The estimated coefficient of β^{KML} remains negative and statistically significant. The slightly lower magnitude implies an annual return premium of −4.85% that is similar to the return premium in the portfolio analysis described above.

Negative return premium for technology shocks embodied in capital has been studied in several papers, e.g., Papanikolaou (2011); Kogan and Papanikolaou (2013, 2014). They focus primarily on the value-growth dimension and the negative premium is associated with firms that have large growth opportunities as they outperform dur-

[43] In comparison to Zhang (2019), where market risk is suggested as the main driving force of the return premium, virtually no significant differences in exposure to market risk are observed here and the market return doesn't explain the returns of the β^{KML}-sorted portfolios. The premium is driven by exposure to capital-embodied technology shocks β^{KML}.

[44] Predictors based on accounting data are dated in year $t-1$ to allow for a lag before the data becomes publicly available. Exceptions are β^{Market} and *Turnover* which are dated at the end of June year t.

[45] I calculate the average return differential by multiplying the estimated coefficient of β^{KML} (−3.617) with the average difference in β^{KML} between the 10th and the 90th percentile (1.536). This average difference in β^{KML} is calculated as time-series average of the interpercentile differences.

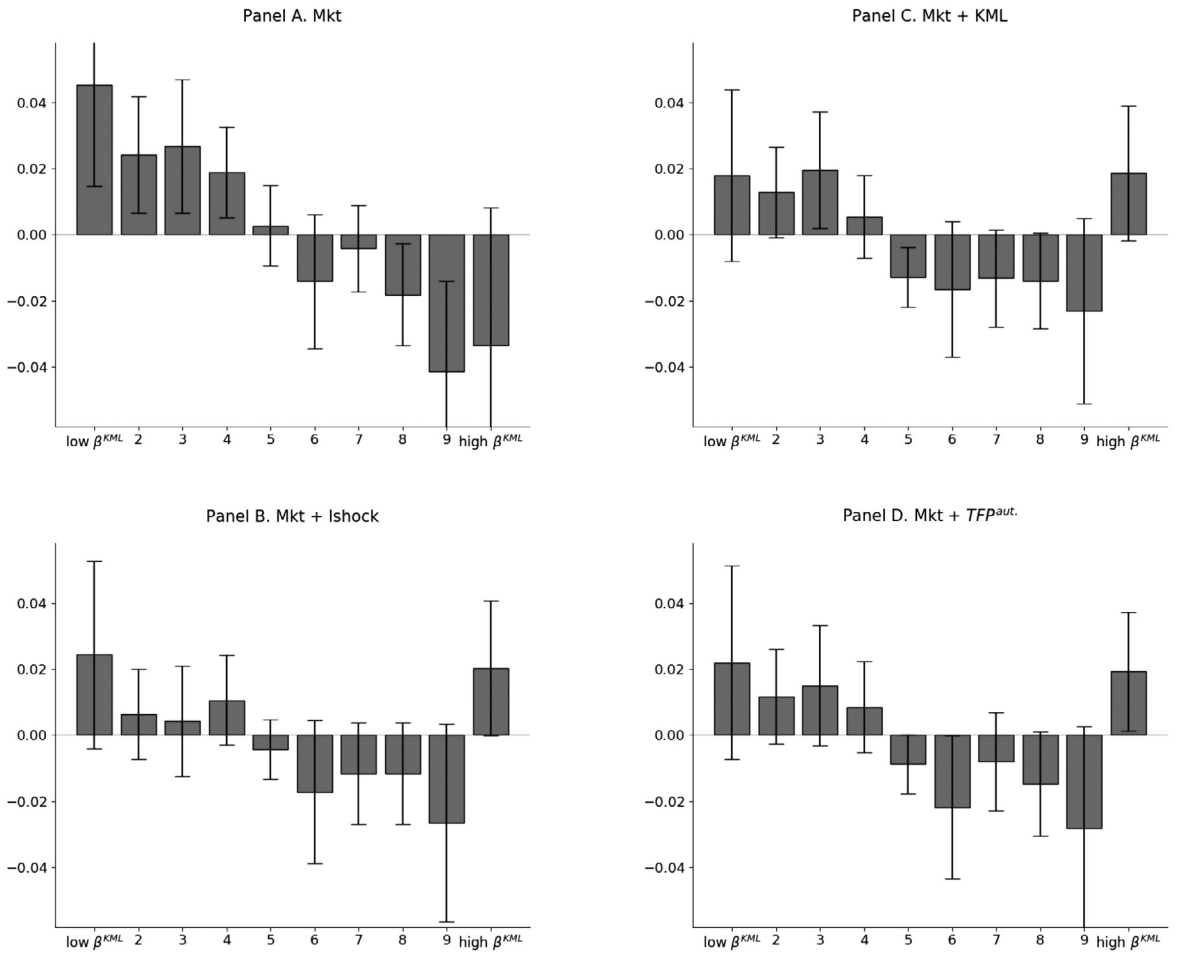


Fig. 7. Fama–MacBeth pricing errors. This figure plots the Fama–MacBeth pricing errors for the ten β^{KML} sorted portfolios for the four different specifications in Table 8. For each portfolio p, the pricing error is defined as time-series average of the annual pricing errors: $\bar{e}_p = \frac{1}{T}\sum_t^T e_{p,t+1}$, where $e_{p,t+1}$ is defined in the regression equation (21). The error bars indicate 90% confidence interval.

ing technology shocks. This mechanism is, to some extent, observable in the fifth portfolio. The portfolio earns negative alpha with respect to CAPM in Panel C in Table 6, but the alpha decreases in Panel D as part of it is accounted for by the portfolio's negative loading on the value factor HML (i.e., positive loading on growth factor).

A large part of the return premium, however, arises from a different mechanism that is concentrated in stocks that underperform during technology shocks and thereby earn higher expected return. These portfolios have negative exposure to technology shocks (see Table 4) and the first two earn positive alpha (see Table 6) after controlling for the value/growth (HML) factor. This provides new evidence of the return premium for technology shocks embodied in capital goods. This observation is valuable as it indicates that capital-embodied technology shocks affect stock returns and pricing of firms in a new dimension complementing the evidence in previous studies focusing mostly on growth opportunities.

I next test whether the measures of technology shocks (I-shock, the KML portfolio and $TFP^{aut.}$) can price the return differences across the β^{KML}-sorted portfolios. I use Fama–MacBeth regressions of this form:

$$R^e_{p,t+1} = \lambda_t^{Mkt}\beta_p^{Mkt} + \lambda_t^A\beta_p^A + \epsilon_{p,t}, \tag{21}$$

where $R^e_{p,t+1}$ is portfolio $p's$ excess return in year $t+1$, β_p^{Mkt} is the portfolio's exposure to aggregate market, and β_p^A is the exposure to one of the three measures of technology shocks (I-shock, KML portfolio or $TFP^{aut.}$).[46] Since the macroeconomic measures I-shock and $TFP^{aut.}$ are available on annual basis, all betas are estimated from the whole time period from 1975 to 2015 using annual data. I normalize the I-shock and $TFP^{aut.}$ measures to have the same standard deviation as the KML portfolio to allow an easy comparison of the estimated magnitudes of λ^A across the different measures of technology shocks. The pricing errors in the underlying portfolios are time-series averages

[46] Although the model abstracts from factor-neutral "market" shock, it can be extended to accommodate such factor. From econometric perspective as well as based on related literature (e.g., Papanikolaou, 2011; Kogan and Papanikolaou, 2014) it is desirable to include market factor in empirical estimation. For this reason, I estimate specification that includes also market factor.

Table 8
Technology-shock risk premium, Fama–MacBeth estimation.

	Mkt	$Mkt + Ishock$	$Mkt + KML$	$Mkt + TFP^{aut.}$
Mkt	0.09	0.088	0.09	0.089
	[0.045,0.135]	[0.041,0.135]	[0.045,0.135]	[0.041,0.137]
$Ishock$		−0.086		
		[−0.141,−0.03]		
KML			−0.049	
			[−0.081,−0.016]	
$TFP^{aut.}$				−0.081
				[−0.145,−0.018]

This table reports the Fama–MacBeth estimates of risk premia of the capital-embodied technology shock A_t and the aggregate stock market risk Mkt_t using ten value-weighted portfolios sorted on β^{KML}. The Fama–MacBeth regressions are specified in Eq. (21), where the dependent variable $R^e_{p,t}$ is the portfolio $p's$ annual excess return in year t and the independent variables are the portfolio exposure to aggregate market risk β^{Mkt}_p and exposure to a measure of capital-embodied technology shocks β^{A}_p. The measure of capital-embodied technology shocks are the I-shock, KML portfolio and TFP^{aut}. The I-shock and $TFP^{aut.}$ measures are normalized to the same standard deviation as the KML portfolio to allow comparison of the estimates. 90% confidence intervals of the estimates $\bar{\lambda}^{Mkt}$ and $\bar{\lambda}^{A}$ based on standard errors with Newey and West (1987) correction are in brackets. The sample period is 1975–2015.

of the annual pricing errors: $\bar{e}_p = (1/T)\sum_t^T e_{p,t+1}$. The test assets are ten β^{KML}-sorted portfolios.

Table 8 reports the estimated market price of risk of technology shocks measured by each of the three measures, $\bar{\lambda}^A = (1/T)\sum_t^T \lambda_t^A$, and aggregate market risk, $\bar{\lambda}^{Mkt} = (1/T)\sum_t^T \lambda_t^{Mkt}$. The specification in column one includes only the market portfolio and suggests a plausible price of market risk of about 9 percent per year. The next three columns show specifications with market and each of the measures of technology shocks A_t. The estimated prices of technology shocks are negative and significant for each of the three measures and range from −4.9% to −8.6%. The observed negative sign of the estimated price of risk of the technology shock A_t justifies the negative sign of the price of risk assumed in my theoretical model.

Fig. 7 shows the pricing errors for the ten β^{KML}-sorted portfolios for each specification from Table 8. The pricing errors in Panel A have a clear pattern of large magnitudes on both sides, which confirms that the market return itself cannot price the cross-section of β^{KML}-sorted portfolios. Panel B-D show that the pricing errors are significantly reduced when a measure of capital-embodied technology shock is included. Hence, each of the three proposed measures appears to price the abnormal returns associated with different exposures to technology shocks.

5.2. Firms' responses to technology shocks

Further, I investigate whether firms with different exposure to technology shocks differ also in their employment, investment and financial performance when the relative prices of capital goods decrease. The model suggests that costly employment and capital adjustments following technology shocks affect firms' financial performance and contribute to firms' risk exposure. To explore this mechanism, I estimate panel regressions of the form:

$$\begin{aligned}\Delta y_{i,t+1} =& constant + b_0 \times Ishock_t + b_1 \times I_{i,t}^{\beta^{KML}} \\ &+ b_2 \times Ishock_t \times I_{i,t}^{\beta^{KML}} + c_0' \times controls_{i,t} \\ &+ c_1 \times TFP_t + e_{i,t+1},\end{aligned} \tag{22}$$

where $\Delta y_{i,t+1}$ is the firm $i's$ change in log employment, capital, capital-labor ratio, or percentage points change in return on capital between years t and $t+1$. $Ishock_t$ is the I-shock measure in year t, $I_{i,t}^{\beta^{KML}}$ is an index indicating the decile of cross-sectionally ranked firm's exposure to technology shocks, $\beta_{i,t}^{KML}$, and $Ishock_t \times I_{i,t}^{\beta^{KML}}$ is their interaction term.[47] $Controls_{i,t}$ is a set of firm-specific control variables consisting of firms' capital, age, book-to-market equity ratio, market capitalization, lagged log cashflow growth at one-year horizon from $t-1$ to t, lagged dependent variable at one-year horizon from $t-1$ to t and firm fixed effects. The regressions include TFP shock as an aggregate control variable.

Panel A in Table 9 reports the results for changes in employment and capital as the dependent variables. The first column shows that a positive technology shock on average decreases firms' employment. The coefficient of the I-shock is negative, statistically significant and economically large. The positive coefficient of the interaction term $Ishock_t \times I_{i,t}^{\beta^{KML}}$ indicates that the adverse effect is significantly stronger for firms with negative exposure to technology shocks. In the next two columns, I split the sample in halves by firms β^{KML} and estimate regression (22) without the interaction term. Firms in the first half are strongly negatively exposed to technology shocks and their employment decreases significantly following a positive technology shock. Firms in the second half have only mild exposure that is much closer to zero and their employment is not affected by these shocks. The coefficient is positive but insignificant.

The following three columns show that technology shocks increase firms' capital. The effect is slightly stronger for firms with $\beta^{KML} \leq median$. This result indicates that lower quality-adjusted prices of capital goods lead to higher investment. Although the difference in the effects on firm capital between firms with $\beta^{KML} \leq median$ and with $\beta^{KML} > median$ is small at the horizon of one year,

[47] See Kogan and Papanikolaou (2014) for a similar approach. The decile index $I_{i,t}^{\beta^{KML}}$ helps mitigate the noise in the independent variable β^{KML}.

Table 9
Firms' one-year response to technology shocks.

Panel A. Changes in employment and capital

	Employment			Capital		
	Full sample	$\beta^{KML} \leq$ median	$\beta^{KML} >$ median	Full sample	$\beta^{KML} \leq$ median	$\beta^{KML} >$ median
$Ishock_t$	−0.672***	−0.342**	0.158	0.703***	0.853***	0.782***
	(0.189)	(0.147)	(0.151)	(0.163)	(0.128)	(0.137)
$Ishock_t \times I_{i,t}^{\beta^{KML}}$	0.105***			0.004		
	(0.036)			(0.032)		
$I_{i,t}^{\beta^{KML}}$	−0.129***	−0.156	−0.070	−0.115*	−0.124	−0.216
	(0.046)	(0.112)	(0.109)	(0.059)	(0.107)	(0.144)
N	48,663	24,616	24,047	48,575	24,604	23,971
R^2	0.286	0.353	0.331	0.327	0.396	0.372

Panel B. Changes in capital-labor ratio and return on capital

	Capital-labor ratio			Return on capital		
	Full sample	$\beta^{KML} \leq$ median	$\beta^{KML} >$ median	Full sample	$\beta^{KML} \leq$ median	$\beta^{KML} >$ median
$Ishock_t$	1.421***	1.269***	0.674***	−0.443***	−0.411***	−0.257***
	(0.192)	(0.151)	(0.198)	(0.050)	(0.041)	(0.059)
$Ishock_t \times I_{i,t}^{\beta^{KML}}$	−0.098**			0.023**		
	(0.042)			(0.009)		
$I_{i,t}^{\beta^{KML}}$	0.001	−0.046	−0.119	−0.035**	−0.018	−0.017
	(0.044)	(0.123)	(0.142)	(0.014)	(0.032)	(0.035)
N	48,575	24,604	23,971	48,487	24,509	23,978
R^2	0.163	0.231	0.233	0.252	0.317	0.314

This table reports the estimates of the panel regression (22) for firm-level changes in log employment and capital in Panel A and changes in log capital-labor ratio and percentage-point changes in return on capital in Panel B, between years t and $t+1$ as specified in the headings. $Ishock_t$ is the I-shock measure in year t, $I_{i,t}^{\beta^{KML}}$ is firm i's exposure to technology shock in year t measured by the decile's index of the cross-sectionally ranked $\beta_{i,t}^{KML}$, and $Ishock_t \times I_{i,t}^{\beta^{KML}}$ is their interaction term. The aggregate and firm-level control variables are included but reported only in Online Appendix Table IA.40. Columns $\beta^{KML} \leq$ median and $\beta^{KML} >$ median show results of the regressions without the interaction term estimated for firms with below and above median β^{KML}, respectively. Standard errors clustered at SIC 4-digit industry level are reported in parentheses. The sample period is from 1975 to 2015.

it becomes bigger when capital investments over horizon of three years from t to $t+3$ are considered.[48] Consequently, technology shocks also increase firms' capital-labor ratio (Panel B). The effect is again stronger for firms with strongly negative exposure, which are generally firms with very high share of displaceable labor. This indicates that negatively-exposed firms indeed adjust, i.e., automate, their processes by decreasing the number of employees and investing in capital when a technology shock occurs.[49] Panel B further shows that firms' return on capital decreases following a positive I-shock, and the effect is larger for negatively exposed firms. These firms experience decrease in return on capital almost twice as large as firms with mild exposure. The estimated coefficients are statistically significant and economically large.

The theoretical model highlights the importance of competition for the economic mechanism how technology shocks affect firm value through costly technology adoption. I focus on this mechanism by solving the model for different degrees of elasticity of substitution for firm-specific goods ν, which governs the intensity of the within-industry competition. While I defer a more detailed discussion to Online Appendix 5.5.9, these variations intuitively predict that the negative effects on income of firms with automation potential will be larger in highly competitive industries. Firms have less market power to retain any rent coming from automation benefits in more competitive industries. The impact of technology shock on firms in capital-intensive sector does not change with the degree of competition as the element of strategic technology adoption is absent in this sector. With this intuition I examine whether the effects of technology shocks on firms' financial performance differ between highly competitive and less competitive industries. I split the sample into two halves by the degree of competition, which I measure by the Herfindahl–Hirschman index (HHI) of sales at the

[48] See Online Appendix Table IA.41. A regression with investment in automation equipment such as machines, software, computers or robots instead of total capital, which is often dominated by plants and structures, may deliver sharper results, but companies do not consistently report investment by detailed capital type. Knesl (2018) differentiates between investment in equipment and investment in structures at the level of manufacturing industries and shows that technology shocks lead to significantly higher investment in equipment in industries with highly displaceable labor while the effects on structures do not differ much.

[49] Table IA.48 in Online Appendix shows the equivalent results for changes in the AP measure itself. These results are consistent with results presented here, but need to be considered with caution due to data comparability aspects as cautioned by BLS: https://www.bls.gov/oes/oes_ques.htm (FAQ, point F.1).

Table 10
Firms' one-year response to technology shocks, highly competitive versus less competitive industries.

Panel A. Return on capital	High AP			Low AP		
	Low HHI	High HHI	All	Low HHI	High HHI	All
$Ishock_t$	−0.439***	−0.377***	−0.500***	−0.214*	−0.254***	−0.224**
	(0.083)	(0.049)	(0.073)	(0.117)	(0.062)	(0.109)
$Ishock_t \times HHI_{i,t}$			0.512**			−0.109
			(0.249)			(0.366)
$HHI_{i,t}$	0.183	−0.028	−0.138	6.712	0.584	0.791
	(3.359)	(0.640)	(0.603)	(5.071)	(0.907)	(0.993)
N	10,652	15,129	25,781	14,627	10,541	25,168
R^2	0.489	0.338	0.362	0.334	0.316	0.286
Panel B. Return on equity						
	High AP			Low AP		
	Low HHI	High HHI	All	Low HHI	High HHI	All
$Ishock_t$	−0.852***	−0.778***	−1.151***	−0.519**	−0.440***	−0.449**
	(0.172)	(0.137)	(0.174)	(0.245)	(0.149)	(0.221)
$Ishock_t \times HHI_{i,t}$			1.780**			−0.362
			(0.815)			(0.916)
$HHI_{i,t}$	−3.999	0.698	0.399	10.171	1.857	1.554
	(7.851)	(1.942)	(1.694)	(11.931)	(2.420)	(2.621)
N	10,652	15,129	25,781	14,627	10,541	25,168
R^2	0.456	0.300	0.321	0.335	0.304	0.282

This table reports the results of regressing firm-level percentage point changes in the return on capital (panel A) and the return on equity (panel B) between years t and $t+1$ on the I-shock measure in year t, $Ishock_t$. The regressions include aggregate TFP shock as an aggregate control variable and firm i's automation potential, capital, age, book-to-market equity ratio, market capitalization, lagged dependent variable at one-year horizon $t-1$ to t, and firm fixed effects as firm-specific control variables. Control variables are included but reported only in Online Appendix Table IA.41. The regressions are estimated for firms with below and above median automation potential $AP_{i,t}$ in industries with high and low competition as indicated. Industries with high and low competition are industries with below and above median Herfindahl–Hirschman index of sales at the SIC 3-digit industry level. Regressions in columns 'All' are estimated for firms with high and low AP, as indicated, across all industries with an interaction term between the I-shock measure and the firm's industry Herfindahl–Hirschman index, $HHI_{i,t}$. Standard errors clustered at industry level are reported in parentheses. The sample period is from 1975 to 2015.

level of SIC 3-digit industries, and estimate the effect of technology shocks on firms with high and low automation potential within each half separately.[50]

Panel A in Table 10 reports the results for percentage point changes in the return on capital over one-year horizon. The first column is for firms with high automation potential in industries with low HHI indicating strong competition. The second column is for similar firms in less competitive industries. The estimated coefficient of the I-shock measure is more negative for firms in more competitive industries. To further show the differential effect, I estimate a regression across firms in all industries with an interaction term between the I-shock measure and the industry's HHI. The interaction term is economically and statistically significant, supporting the results in the first two columns. The following three columns show the results for firms with low automation potential in competitive and less competitive industries. The estimated coefficient of the I-shock measure is again negative, but the coefficient of the interaction term is close to zero. Panel B shows an equivalent set of results for changes in return on equity, which are generally consistent. This suggests that holding firms' automation potential relatively constant, the within-industry competition increases the negative effect of technology shocks on firms' financial performance.

While my model assumes that firms are ex-ante identical within-industries, it is natural that firms empirically differ also within industries (Table 1) for variety of reasons including, e.g., staggered technology adoption, where some firms already automated in the past, while others are likely to automate going forward. I explore whether variation in automation potential within industries relates to real variables (employment, investment, capital-labor ratio, and ROA) in three ways. Specifically, I sort within industries on exposure to the KML portfolio, β^{KML}, using traditional monthly regressions, and also using weekly regressions as suggested by Kogan and Papanikolaou (2014). I also sort within industries on the AP measure. For brevity, I report only the results based on traditional β^{KML} in Table 11. The results for the other two sorts are presented in the Online Appendix 8. The overall message of these results is that even variation within industries in these different measures has some ability to predict real outcomes. For example, employment decreases, while capital-labor ratio increases for firms with low within-industry β^{KML} follow-

[50] Measuring competition within industries is empirically not a straightforward task due to various aspects of products, firms, markets and industries. Herfindahl–Hirschman index is an imperfect approximation (Syverson, 2019). Its advantage is the availability of the necessary data for the whole time period.

Table 11
Firms' one-year response to technology shocks, within-industry by β^{KML}.

Panel A. Changes in employment and capital	Employment			Capital		
	Full sample	$\beta^{KML,w} \leq$ median	$\beta^{KML,w} >$ median	Full sample	$\beta^{KML,w} \leq$ median	$\beta^{KML,w} >$ median
$Ishock_t$	−0.385***	−0.231*	−0.030	0.754***	0.801***	0.731***
	(0.137)	(0.121)	(0.142)	(0.113)	(0.100)	(0.115)
$Ishock_t \times I_{i,t}^{\beta^{KML,w}}$	0.035			−0.017		
	(0.023)			(0.021)		
$I_{i,t}^{\beta^{KML,w}}$	−0.042*	−0.104	0.024	−0.065***	−0.043	−0.031
	(0.024)	(0.078)	(0.072)	(0.025)	(0.071)	(0.071)
N	48,663	24,357	24,306	48,575	24,313	24,262
R^2	0.305	0.368	0.370	0.360	0.423	0.412

Panel B. Changes in capital-labor ratio and return on capital	Capital-labor ratio			Return on capital		
	Full sample	$\beta^{KML,w} \leq$ median	$\beta^{KML,w} >$ median	Full sample	$\beta^{KML,w} \leq$ median	$\beta^{KML,w} >$ median
$Ishock_t$	1.151***	1.059***	0.856***	−0.388***	−0.361***	−0.320***
	(0.150)	(0.138)	(0.157)	(0.062)	(0.057)	(0.055)
$Ishock_t \times I_{i,t}^{\beta^{KML,w}}$	−0.042*			0.010		
	(0.021)			(0.008)		
$I_{i,t}^{\beta^{KML,w}}$	−0.027	0.060	−0.039	0.003	0.000	0.025
	(0.026)	(0.078)	(0.072)	(0.008)	(0.028)	(0.030)
N	48,575	24,313	24,262	48,487	24,269	24,218
R^2	0.168	0.241	0.248	0.277	0.352	0.347

This table reports the estimates of the panel regression (22) with β^{KML} sorted within industries for firm-level changes in log employment and capital in Panel A and changes in log capital-labor ratio and percentage-point changes in return on capital in Panel B, between years t and $t+1$ as specified in the headings. $Ishock_t$ is the I-shock measure in year t, $I_{i,t}^{\beta^{KML,w}}$ is firm i's exposure to technology shock within industry in year t measured by the decile's index of the cross-sectionally ranked $\beta_{i,t}^{KML}$ within industry, and $Ishock_t \times I_{i,t}^{\beta^{KML,w}}$ is their interaction term. The aggregate and firm-level control variables are included but not reported. Columns $\beta^{KML,w} \leq$ median and $\beta^{KML,w} >$ median show results of the regressions without the interaction term estimated for firms with below and above median β^{KML}, respectively. Standard errors are reported in parentheses. The sample period is from 1975 to 2015.

ing a technology shock. A deeper investigation of within-industry effects may be a potential avenue for future theoretical and empirical research.

6. Conclusion

Firms' potential to substitute cheaper capital for some types of labor, i.e., automation, is an important source of changes in the economy. I find that firms' potential to automate the production process is an important determinant of firms' exposure to technology shocks embodied in capital. I show that these shocks are a significant driver of the dynamics and the cross-section of stock returns.

In a competitive environment, firms automatable labor increases riskiness. Automation becomes a costly necessity for firms and erodes potential rents from technological improvements, while efficiency gains are passed on to consumers. Empirically, firms with higher AP measures have strong negative exposures to technology shocks, and their returns are informative about technology shocks.

This paper abstracts from other aspects such as market entry, managerial ability to adopt new technology or operating leverage, which are certainly relevant in some real world scenarios and worth exploring both empirically and theoretically. Future research can also focus on a dynamic setting with an endogenous arrival of technological improvements. Factors that determine winners of technological transformation among firms are of interest as well and can speak to changes in market power and evolution of firm and industry size.

Data availability

Automation and the Displacement of Labor by Capital: Asset Pricing Theory and Empirical Evidence (Original data) (Mendeley Data).

The data and code for this article can be found at https://doi.org/10.17632/by8r2znnpt.1.

Appendix A. Equilibrium conditions

The firm-specific goods, $Y_{f,s,t}$, are combined to sector-specific goods, $Y_{s,t}$, using a constant elasticity-of-substitution (CES) function:

$$Y_{s,t} = \left(\int_0^1 Y_{f,s,t}^{\frac{\nu-1}{\nu}} df \right)^{\frac{\nu}{\nu-1}}, \tag{A.1}$$

where ν is the elasticity of substitution between the firm-specific goods. It allows to express the prices of the sector-specific goods, $P_{s,t}$, with prices of firm-specific goods, $P_{f,s,t}$, as:

$$P_{s,t} = \left(\int_0^1 P_{f,s,t}^{1-\nu} df \right)^{\frac{1}{1-\nu}}. \tag{A.2}$$

The CES aggregator technology at the sector level implies an optimal demand functions for the firm-specific goods:

$$Y_{f,s,t} = \left(\frac{P^l_{f,s,t}}{P_{s,t}}\right)^{-\nu} Y_{s,t} \quad \text{and} \quad Y_{f,s,t} = \left(\frac{P^k_{f,s,t}}{P_{s,t}}\right)^{-\nu} Y_{s,t}$$

$$\text{for} \quad s = 1,\ 2 \text{ and } t = 1,\ 2. \tag{A.3}$$

The sector goods are combined to an aggregate final consumption good, $Y_{C,t}$, using a CES function with an elasticity of substitution ρ:

$$Y_{C,t} = \left(\sum_{s=1}^{2} Y_{s,t}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}. \tag{A.4}$$

The CES aggregator at the aggregate level implies an optimal demand function for the sector-specific goods:

$$Y_{s,t} = \left(\frac{P_{s,t}}{P_{A,t}}\right)^{-\rho} Y_{A,t} \tag{A.5}$$

The first order conditions of firms' optimization in (7) and (8) imply that firms charge constant mark-ups over the marginal production cost:

$$P^l_{f,s,t} = \frac{\nu}{\nu-1} W_{s,t} \quad \text{and} \quad P^k_{f,s,t} = \frac{\nu}{\nu-1} P^I_{s,t}. \tag{A.6}$$

The first order condition of households' optimization determines the optimal labor effort as:

$$H_{h,s,t} = \left(\chi^{-1} W_{s,t}\right)^{\frac{1}{\theta}} \quad s \in \{1,2\}. \tag{A.7}$$

Market clearing condition for the aggregate good is defined as

$$\sum_{h=1}^{N_h} c_{h,t} = Y_{A,t}. \tag{A.8}$$

Market clearing on the labor markets is defined as:

$$\begin{aligned}
&s = 1, t = 1: \quad L^l_{1,1} = \sum_{h=1}^{N_h} L_{h,1,1} \\
&s = 1, t = 2: \quad L^l_{1,2} + L^k_{1,2} = \sum_{h=1}^{N_h} L_{h,1,2} \\
&s = 2, t = 1, 2: \quad L^k_{2,t} = \sum_{h=1}^{N_h} L_{h,2,t},
\end{aligned} \tag{A.9}$$

where $L^l_{s,t}$ is labor used directly in goods production in sector s and $L^k_{s,t}$ is labor used in production of capital in sector s. The market clearing on the capital investment market is:

$$\begin{aligned}
&s = 1: \int_0^1 K_{f,1,2} \mathbb{1}\{\text{Automated=Yes}\}_{f,1,2} df = K^{\alpha}_{1,2}, \\
&s = 2: \int_0^1 K_{f,2,t} df = K^{\alpha}_{2,t} \quad \text{for} \quad t = 1,\ 2.
\end{aligned} \tag{A.10}$$

For Nash-type equilibrium δ^* in sector $s = 1$ at $t = 2$, define equilibrium price and quantity:

$$P_{1,2}(\delta^*) = \left({P^k_{f,1,2}}^{1-\nu} \delta^* + {P^l_{f,1,2}}^{1-\nu} (1-\delta^*)\right)^{\frac{1}{1-\nu}} \tag{A.11a}$$

$$\text{and} \quad Y_{1,2}(\delta^*) = \left({Y^k_{f,1,2}}^{\frac{\nu-1}{\nu}} \delta^* + {Y^l_{f,1,2}}^{\frac{\nu-1}{\nu}} (1-\delta^*)\right)^{\frac{\nu}{\nu-1}}. \tag{A.11b}$$

Appendix B. Construction of routine task intensity

The Routine Task Intensity measures the importance of routine tasks in a given occupation. The original measure was calculated for 330 occupations based on data from the Dictionary of Occupational Titles (DOT) 1977 (Autor and Dorn, 2013). I develop a new and more detailed version of the RTI measure based on occupational characteristics from the majority of the O*Net releases and describe the underlying data with other details in Online Appendix 3.3.1. This improves the RTI measure in several dimensions. First, using multiple releases of O*NET allows to capture changes in occupational characteristics within occupations over time as technological progress and automation can change individual tasks within occupations (Autor et al., 2003). Second, I calculate the RTI measure for a larger number of more detailed occupations (up to 731 instead of previous 330). Third, I use a larger set of underlying occupational characteristics (30 instead of 5), which allows a more robust measurement of the importance of each type of tasks.

To calculate the RTI measure, I select 30 occupational descriptors and group them into descriptors measuring abstract, routine and manual tasks, which is analogous to the original approach in Autor and Dorn (2013). I report the full list of the descriptors including the corresponding scales of measurement in Online Appendix Table IA.5. I calculate the routine, abstract and manual task inputs for each occupation by averaging the scores of the corresponding descriptors as follows:

$$T^j_{occ,t} = \frac{1}{N_j} \sum_{i \in N_j} Descriptor_{occ,t,i}$$

$$j \in \{Routine,\ Manual,\ Abstract\}, \tag{B.1}$$

where $T^j_{occ,t}$ is the input of task j in occupation occ at time t and N_j is the set of descriptors for $j's$ task input. Using the task inputs, I calculate the RTI for each occupation as

$$RTI_{occ,t} = ln\left(T^R_{occ,t}\right) - ln\left(T^M_{occ,t}\right) - ln\left(T^A_{occ,t}\right). \tag{B.2}$$

Following Autor and Dorn (2013), occupations ranked by RTI in the top third are denoted as routine intensive: $RTI_{occ,t} > RTI^{66}_t$, where RTI^{66}_t denotes the 66th percentile of RTI weighted by US national occupation employment.

Appendix C. Discussion of the model

I briefly discuss some aspects of the theoretical model. First, this paper focuses on the transition of firms from labor-based to capital-based production that is driven by technology shocks. An analysis of such transition requires a comparison of firms at two different points in time. The two-period model allows to incorporate the strategic choices of firms which are the main driving force while allowing the required analysis. The empirical analysis shows that there are a few major technology shocks over the last four decades, and the model applies to the transition of firms during these periods of fast technological progress.

Second, although the mixed-strategy equilibrium provides interesting insight, it itself is not necessary for the main asset pricing implications that are the main focus of

the model and subsequent empirical analysis. If the model is altered so that the mixed-strategy equilibrium disappears, there would be still two possible outcomes. One for low or no technology shock, where no firm would automate and one for large technology shocks, where all firms automate. The mixed-strategy equilibrium only generalizes the case of pure-strategy equilibrium to a mixed-strategy case, although for tractability reasons in arguably a parsimonious and stylized way. For the same reason, it is less relevant whether capital is supplied competitively or with decreasing or constant returns to scale. It is the product market competition between monopolistically competing firms that erodes the rent associated with automation.

Third, since the idiosyncratic labor productivity shock $\tilde{\epsilon}_h$ is mean-preserving, the aggregate technology shock, A^{high}, increases the average wage. Although this might be considered counter-factual with the evidence suggesting decreasing labor share over recent years (see e.g., Karabarbounis and Neiman, 2013), it is a conservative approach for the asset pricing implications and facilitates tractability in the model. Since the focus is on the negative premium, a technology shock that would dampen wages (e.g., through negative-mean idiosyncratic labor productivity shocks) would magnify the negative premium. Online Appendix 2 provides further discussion and comparison to the model in Zhang (2019).

The data and code for this article can be found at https://doi.org/10.17632/by8r2znnpt.1.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.11.003

References

Acemoglu, D., Pascual, R., 2020. Robots and jobs: evidence from us labor markets. J. Polit. Econ. 128 (6), 2188–2244. doi:10.1086/705716.

Aumann, R.J., 1964. Markets with a continuum of traders. Econometrica 32 (1/2), 39–50.

Aumann, R.J., 1966. Existence of competitive equilibria in markets with a continuum of traders. Econometrica 34 (1), 1–17.

Autor, D., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. 103 (5), 1553–1597. doi:10.1257/aer.103.5.1553.

Autor, D.H., 2013. The "Task Approach" to Labor Markets: An Overview. Technical Report. National Bureau of Economic Research.

Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. Am. Econ. Rev. 96 (2), 189–194. doi:10.1257/aer.103.5.1553.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (4). doi:10.1162/003355303322552801.

Broda, C., Weinstein, D.E., 2010. Product creation and destruction: evidence and price implications. Am. Econ. Rev. 100 (3), 691–723. doi:10.1257/aer.100.3.691.

Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. WW Norton & Company.

Constantinides, G.M., Duffie, D., 1996. Asset pricing with heterogeneous consumers. J. Polit. Econ. 104 (2), 219–240. doi:10.1086/262023.

Constantinides, G.M., Ghosh, A., 2017. Asset pricing with countercyclical household consumption risk. J. Finance 72 (1), 415–460. doi:10.1111/jofi.12471.

Cummins, J.G., Violante, G.L., 2002. Investment-specific technical change in the United States (1947–2000): measurement and macroeconomic consequences. Rev. Econ. Dyn. 5 (2), 243–284.

Eisfeldt, A.L., Rampini, A.A., 2006. Capital reallocation and liquidity. J. Monet. Econ. 53 (3), 369–399. doi:10.1016/j.jmoneco.2005.04.006.

Eisfeldt, A.L., Rampini, A.A., 2007. New or used? Investment with credit constraints. J. Monet. Econ. 54 (8), 2656–2681. doi:10.1016/j.jmoneco.2007.06.030.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81 (3), 607–636.

Fisher, J.D.M., 2006. The dynamic effects of neutral and investment-specific technology shocks. J. Polit. Econ. 114 (3), 413–451. https://doi.org/10.1086/505048

Garlappi, D. R., McCully, C. P., 2016. Concepts and methods of the U.S. national income and product accounts

Garlappi, L., Song, Z., 2016. Can investment shocks explain the cross section of equity returns? Manag. Sci. 63 (11), 3829–3848. doi:10.1287/mnsc.2016.2542.

Garlappi, L., Song, Z., 2017. Capital utilization, market power, and the pricing of investment shocks. J. Financ. Econ. 126 (3), 447–470. doi:10.1016/j.jfineco.2016.11.006.

Gârleanu, N., Kogan, L., Panageas, S., 2012. Displacement risk and asset returns. J. Financ. Econ. 105 (3), 491–510. doi:10.1016/j.jfineco.2012.04.002.

Gârleanu, N., Panageas, S., 2017. Finance in a time of disruptive growth.

Garleanu, N., Panageas, S., Yu, J., 2012. Technological growth and asset pricing. J. Finance 67 (4), 1265–1292. doi:10.1111/j.1540-6261.2012.01747.x.

Greenwood, J., Hercowitz, Z., Huffman, G.W., 1988. Investment, capacity utilization, and the real business cycle. Am. Econ. Rev. 78 (3), 402–417.

Greenwood, J., Hercowitz, Z., Krusell, P., 1997. Long-run implications of investment-specific technological change. Am. Econ. Rev. 87 (3), 342–362.

Greenwood, J., Hercowitz, Z., Krusell, P., 2000. The role of investment-specific technological change in the business cycle. Eur. Econ. Rev. 44 (1), 91–115.

Greenwood, J., Jovanovic, B., 1999. The information-technology revolution and the stock market. Am. Econ. Rev. 89 (2), 116–122. doi:10.1257/aer.89.2.116.

Greenwood, J., Yorukoglu, M., 1997, 1974. Carnegie-Rochester Conference Series on Public Policy, vol. 46. Elsevier, pp. 49–95.

Guvenen, F., Ozkan, S., Song, J., 2014. The nature of countercyclical income risk. J. Polit. Econ. 122 (3), 621–660. doi:10.1086/675535.

Hobijn, B., Jovanovic, B., 2001. The information-technology revolution and the stock market: evidence. Am. Econ. Rev. 91 (5), 1203–1220. doi:10.1257/aer.91.5.1203.

Hornstein, A., Krusell, P., 1996. Can technology improvements cause productivity slowdowns? NBER Macroecon. Annu. 11, 209–259.

Hou, K., Xue, C., Zhang, L., 2017. Replicating anomalies. Rev. Financ. Stud. doi:10.1093/rfs/hhy131.

Jacobson, L.S., LaLonde, R.J., Sullivan, D.G., 1993. Earnings losses of displaced workers. Am. Econ. Rev. 83 (4), 685–709.

Jovanovic, B., Rousseau, P.L., 2002. The q-theory of mergers. Am. Econ. Rev. 92 (2), 198–204. doi:10.1257/000282802320189249.

Jovanovic, B., Rousseau, P.L., 2005. General purpose technologies. In: Handbook of Economic Growth, vol. 1. Elsevier, pp. 1181–1224. doi:10.1016/S1574-0684(05)01018-X.

Jovanovic, B., Rousseau, P.L., 2008. Mergers as reallocation. Rev. Econ. Stat. 90 (4), 765–776.

Karabarbounis, L., Neiman, B., 2013. The global decline of the labor share. Q. J. Econ. 129 (1), 61–103. doi:10.1093/qje/qjt032.

Knesl, J., 2018. Job displacement through technology, how technological shocks affect households' income and unemployment.

Kogan, L., Papanikolaou, D., 2013. Firm characteristics and stock returns: the role of investment-specific shocks. Rev. Financ. Stud. 26 (11), 2718–2759. doi:10.1093/rfs/hht026.

Kogan, L., Papanikolaou, D., 2014. Growth opportunities, technology shocks, and asset prices. J. Finance 69 (2), 675–718. doi:10.1111/jofi.12136.

Kogan, L., Papanikolaou, D., Schmidt, L., Song, J., 2018. Technological innovation and the distribution of labor income growth.

Kogan, L., Papanikolaou, D., Stoffman, N., 2020. Left behind: creative destruction, inequality, and the stock market. J. Polit. Econ. 128 (3). doi:10.1086/704619. 000–000

Lin, X., Palazzo, B., Yang, F., 2020. The risks of old capital age: asset pricing implications of technology adoption. J. Monet. Econ. 115, 145–161. doi:10.1016/j.jmoneco.2019.06.001.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703.

Papanikolaou, D., 2011. Investment shocks and asset prices. J. Polit. Econ. 119 (4), 639–685. doi:10.1086/662221.
Pástor, L., Veronesi, P., 2009. Technological revolutions and stock prices. Am. Econ. Rev. 99 (4), 1451–1483. doi:10.1257/aer.99.4.1451.
Schmidt, L., 2016. Climbing and falling off the ladder: asset pricing implications of labor market event risk.
Shumway, T., 1997. The delisting bias in CRSP data. J. Finance 52 (1), 327–340. doi:10.1111/j.1540-6261.1997.tb03818.x.
Stevens, A.H., 1997. Persistent effects of job displacement: the importance of multiple job losses. J. Labor Econ. 15 (1, Part 1), 165–188.
Syverson, C., 2019. Macroeconomics and market power: context, implications, and open questions. J. Econ. Perspect. 33 (3), 23–43.
Topel, R., 1990. Specific capital and unemployment: measuring the costs and consequences of job loss. In: Carnegie-Rochester Conference Series, vol. 33. Elsevier, pp. 181–214.
Topel, R., 1991. Specific capital, mobility, and wages: wages rise with job seniority. J. Polit. Econ. 99 (1), 145–176. doi:10.1086/261744.
Wasshausen, D., Moulton, B.R., et al., 2006. The Role of Hedonic Methods in Measuring Real GDP in the United States. Technical Report. Bureau of Economic Analysis.
Zhang, M.B., 2019. Labor-technology substitution: implications for asset pricing. J. Finance doi:10.1111/jofi.12766.