Are we running out of exhaustible resources?

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Abstract

Mineral and material commodities are essential inputs to economic production, but there have been periodical concerns about mineral scarcity. However, there has been no systematic recent study that has determined whether mineral commodities have become scarcer over the longer run. Here we provide systematic evidence that worldwide, near-term exhaustion of economically valuable commodities is unlikely. We construct and analyse a new database of 48 economically-relevant commodities from 1957–2015, including estimates of worldwide production, reserves and reserve bases, prices, and production, using publicly-available data and further data requested from the United States Geological Survey. We explore trends in prices, reserves-to-production ratios, and production itself, on a commodity-by-commodity basis, using econometric techniques allowing for structural changes, and further estimate overall trends robust to outlying observations. For almost all commodities, we cannot reject the null hypothesis of no trend in prices and exhaustion, while production has increased. Price signals appear to have guided consumption and provided incentives for innovation and substitution. Concerns about mineral depletion therefore appear to be less important than concerns about externalities, such as pollution and conflict, and ecosystem services (e.g. climate stability) where price signals are often absent.

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1 Introduction

In the late 18th century, Malthus (1798) set out the view that resource constraints and population growth would drive living standards to a subsistence level. Resource availability was a mainstream concern in the 1960s and 1970s (Barnett and Morse 1963, Meadows et al 1972; Ehrlich and Holdren, 1971; Simon, 1981). Fears about mineral and material resource availability are periodically reiterated (Meadows et al. 1992, Meadows and Randers, 2012); recent examples include metals for low-carbon products (EC, 2017; UNEP 2016), declining grades of resources on land (Calvo et al. 2016), and security of supply (Northey et al. 2014). The counter to such fears is that when mineral availability is limited, prices rise. When prices are high, consumers increase efficiency and substitute to other materials (Dasgupta and Heal, 1974), and suppliers innovate and find ways to access new resources.

Questions about the availability of mineral and material commodities persist today because of a paucity of recent systematic empirical analysis of long run data. To remedy this, we study trends in exhaustion by creating and analysing a new dataset by assembling, cleaning, and digitizing six decades of analogue annual data from the US Geological Survey (USGS) Mineral Commodity Summaries (MCS) from 1957-2015 on 83 mineral or material commodities (referred to hereafter as 'minerals'), from Antimony to Zinc. After correcting many measurement errors and inconsistencies, and making other adjustments (e.g. for inflation and standardising to a common unit of measurement), the resulting dataset contains production, price, reserves, reserve base, and resources information for 48 minerals in consistent quantity- (metric tons) and price-units (2010 USD/metric ton) units.

Economic models suggest a variety of possible production and price trajectories for (optimally extracted) exhaustible resources depending on how production costs change and how easily new reserves can be found over time. Once a resource is approaching economic exhaustion, economic models suggest that resource prices should rise (Krautkraemer, 1998; Livernois, 2008, Pindyck 1978, Slade 1982). Exploring changes in prices to date, most empirical studies have found little evidence of such price increases (e.g. Smith 1979, Berck and Roberts, 1995; Ahrens and Sharma 1997; Lee, List, and Strazicich 2006). Rising resource prices are not necessary and sufficient indicators of impending exhaustion. For instance, markets for some commodities are far from perfectly competitive, and shocks and geopolitical factors can drive prices up without any underlying scarcity. Short-run instabilities in price trends imply that prices should not be the sole indicator of scarcity (see Smith 1978 for an early discussion). The converse is that long-run scarcity does not necessarily imply rising prices in the short to medium term; prices will rise once it becomes clear that exhaustion is near and the potential for substitution to other materials is very limited. Declining production might occur if the mineral becomes more difficult and expensive to extract (Devarajan and Fisher 1982, Pindyck, 1978; Kirchherr et al. 2017), or if demand falls (due to prices increases or due to substitution possibilities, Tilton 1990). Further, a declining reserves-to-production ratio implies that increases in new reserves are not keeping up with increases in production; if this continues, reserves will be exhausted. Some economic models suggest that technological change and substitution potentials may prevent humanity from exhausting key resources for a long time (Schwerhoff and Stuermer, 2016; Lin and Wagner 2007). On the other hand, Earth's mineral resources are finite, so as time approaches infinity, a 'circular economy' (Kirchherr et al. 2017) model is likely to be necessary. But this is not inconsistent with the view that 'non-renewable resources are, within a time frame relevant for humanity, practically inexhaustible.' (Schwerhoff and Stuermer 2015).

We explore trends in prices, reserves-to-production ratios, and production of mineral commodities using econometric techniques allowing for structural changes, and further estimate overall trends robust to outlying observations. If all three features are absent, i.e. a resource has non-declining annual production, a non-declining reserves-to-production ratio, *and* non-increasing prices, it is unlikely that the resource is approaching exhaustion. Our results show that for almost all commodities, we cannot reject the null hypothesis of no trend in prices and exhaustion, while production has increased. Price signals appear to have guided consumption and provided incentives for innovation and substitution. Our findings suggest that concerns about mineral depletion are less important than concerns about externalities, such as pollution and conflict, and ecosystem services (e.g. climate stability) where price signals are often absent.

In Section 2, we present the data. Section 3 describes our econometric approach. Section 4 explains the main results and Section 5 concludes. The appendix provides further model details, additional model specifications, and robustness checks.

2 Data

We construct a novel database on mineral commodity resources, reserves, reserve base, production, and prices, by combining observations from the comprehensive set of USGS Mineral Commodity Summaries (MCS) from 1957-2015. *Resources*, in the context of the USGS, are defined as the concentration of a commodity in or on Earth's crust in such form and amount that economic extraction of this commodity from the concentration is currently or potentially feasible. *Reserve Base* is defined as that part of an identified resource that meets specified minimum physical and chemical criteria related to current mining and production practices. The reserve base includes those resources that are currently economic (*Reserves*), marginally economic (*Marginal Reserves*), and some of those that are currently sub-economic (*Sub-economic Resources*). *Production* refers to the annual economic extraction of the commodity in each year. Reserves-to-production ratios are calculated as the ratio of annual *Reserves* to annual *Production* and capture the remaining years of a particular commodity at current rates of production. Combining such a wide range of measurements increases the risk of measurement error. In our models we therefore employ robust estimation techniques to identify the presence (and remove the influence of) outlying observations. Where an outlier was identified in estimation (see econometric approach), the data point was manually double-checked in the original report and where an extraction error (typographical or unit error, etc.) was discovered that error was corrected.[5] Data in the USGS reports were excluded from our dataset where they were obviously erroneous (e.g. reserves in the 1980-87 period) or where a qualitative reason justified exclusion. Outliers that did not meet these exclusion criteria remain in the dataset and are managed by the robust statistical techniques described in our methods.

To ensure a sufficient number of observations over time, we restrict our analysis to commodities with at least 25 years of observations for production and reserves or reserve base. The resulting dataset of 48 commodities (see Figures 1 & 2 or Appendix F for a list) was subsequently independently quality controlled for data entry errors by at least two different research assistants. Production, reserves, and resource data was converted to metric tons and prices were standardised as USD/metric ton in constant 2010 US dollars (using the GDP deflator). Resulting data is plotted in Figures 1 and 2, showing a price index of inflation-adjusted of inflation-adjusted commodity prices in constant 2010 USD and reserves-to-production ratios as well as a production index relative to the first available observation. Visual inspection of our dataset suggests that over the last 50 years prices and reserves-to-production ratios have been predominantly steady (Figures 1 & 2) while production (Figure 2, bottom) has significantly increased.

[5] Specific manual adjustments were also made to the following minerals. Barite: observation in 1959 removed due to reserve only including expert reserves for USA. Molybdenum: observation in 1957 removed due to reserves only including USA and Chile. Phosphate Rock: 1974 and 1980-1982 removed due to reporting inconsistencies in MCS reports. Rare Earths: 1957-1972 removed due to reporting inconsistencies in MCS reports.

Figure 1: Price Index of Commodities from 1957-2014 based on constant 2010 USD. The index is constructed relative to the first available observation of each commodity.

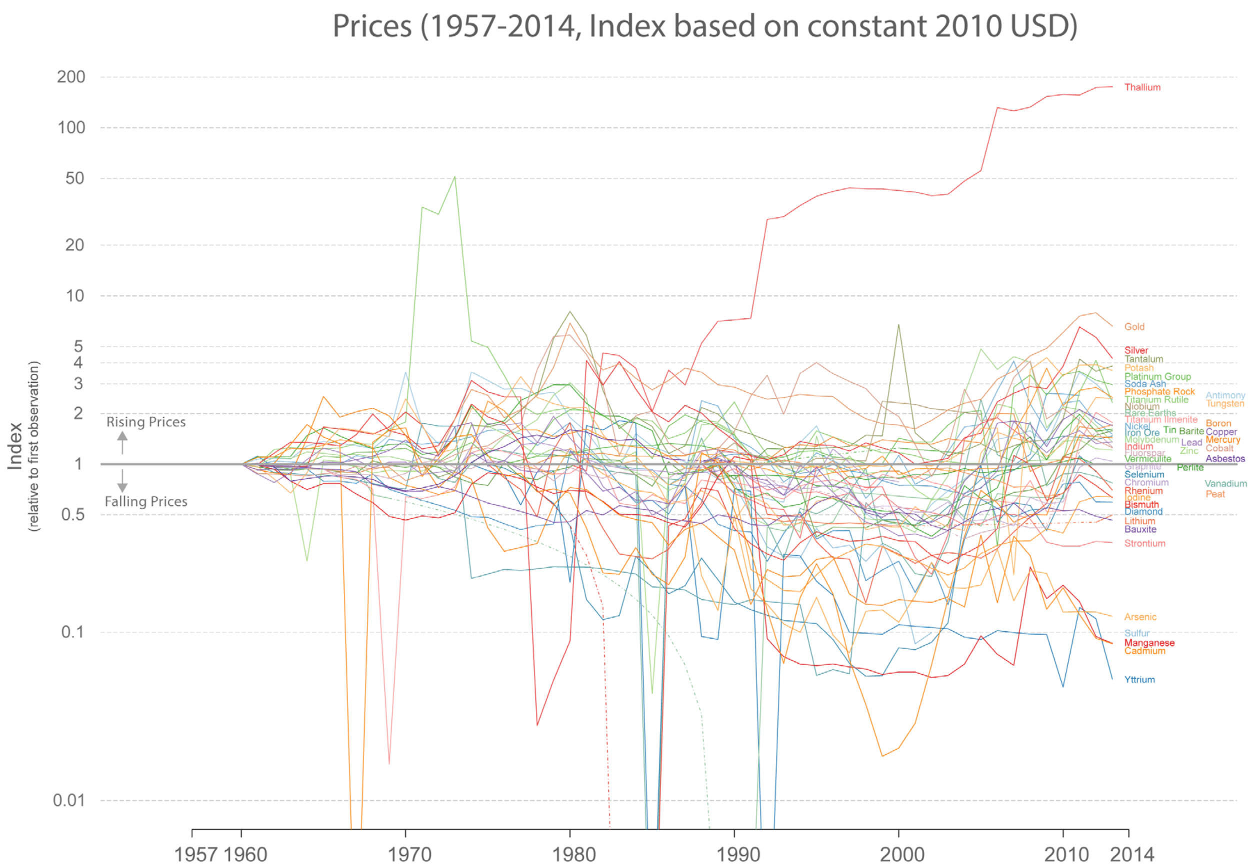
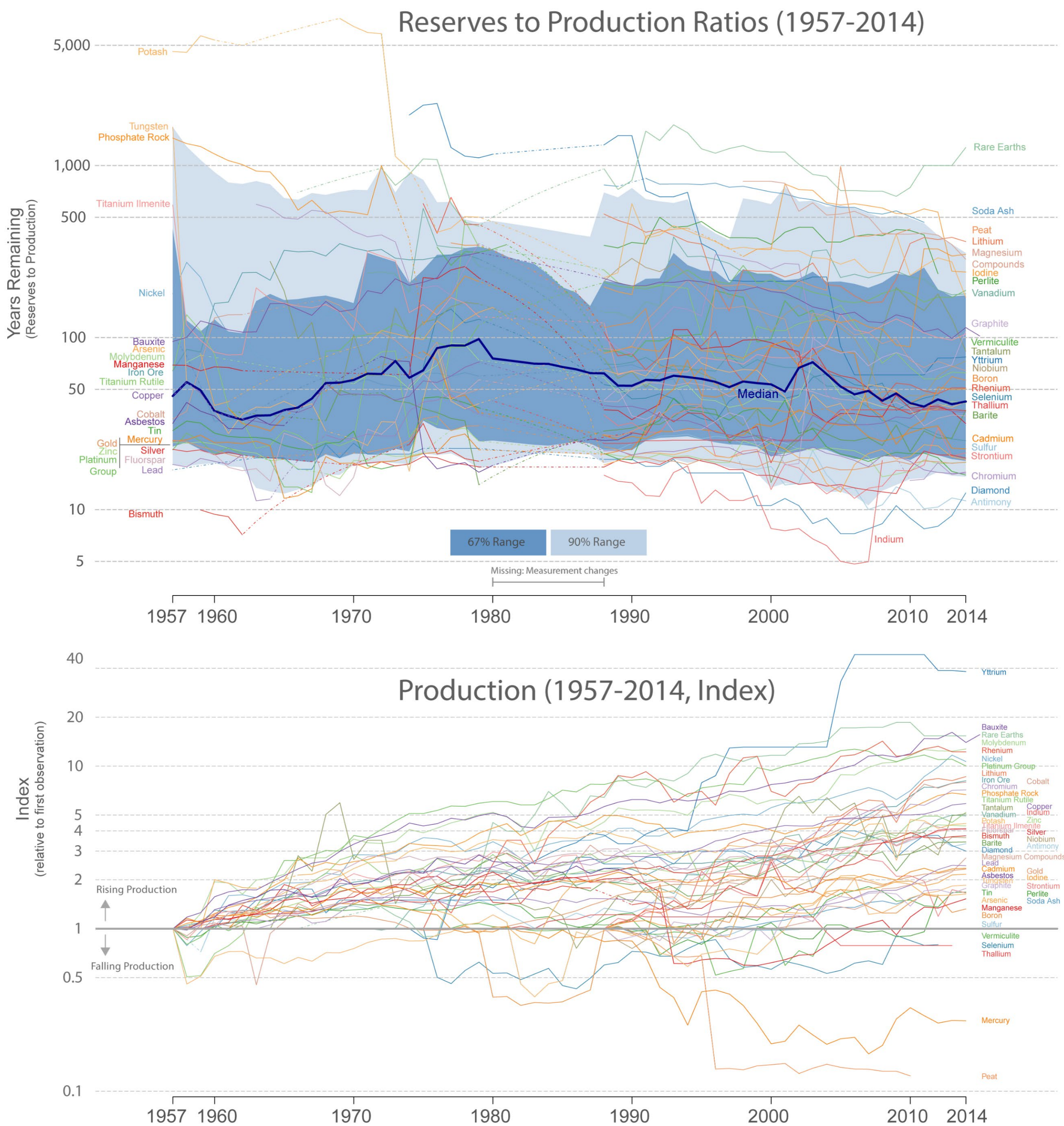


Figure 2: Reserves-to-production Ratios from 1957-2014 (top panel) and production index relative to the first available observation for each resource (bottom panel). Missing periods are shown as dashed interpolated values (these interpolated values are not used in the statistical analysis of trends). The reserves-to-production ratios are stable over the entire sample with a median around 50 years, while production has increased for most commodities – see trend estimates in Figures 3, 4, and 5.



3. Econometric Approach

We formally test whether there are any measurable trends in prices, reserves-to-production ratios, as well as production, and whether such trends are stable over time and common across commodities, using econometric methods that enable identification of trends in a manner that is robust to structural changes and outlying observations. The base model for each commodity is specified as equation (1) in levels and (2) in first differences:

$$y_{i,t} = \mu_i + \beta_{i,t} t + \epsilon_{i,t} \quad (1)$$

$$\Delta y_{i,t} = \beta_{i,t} + \mathrm{u}_{i,t} \quad (2)$$

where Δ refers to the difference operator and $y_{i,t}$ denotes the natural log of the reserves-to-production ratio, production, or prices of commodity *i* at time *t* and $\epsilon_{i,t}$ and $\mathrm{u}_{i,t}$ are unobserved error terms. The parameter μ_i denotes the intercept in levels, and $\beta_{i,t}$ is the (potentially time-varying) coefficient on a linear time trend (or drift) and the parameter of interest in our analysis. We focus on tests of linear time trends/drifts as these have power against a wide range of trends in any moment of the distribution of $y_{i,t}$ (Busetti and Harvey 2008, Gonzalo and Rivas 2020). In (1), a coefficient $\beta_{i,t} \neq 0$ for some *t* implies the presence of a (temporary) trend, with $\beta_{i,t} = \beta_i \; \forall t$ implying a stable trend over time. Estimating $\beta_{i,t}$ in (2) corresponds to model allowing for linear trend in levels of $y_{i,t}$, or a drift if $y_{i,t}$ contains a stochastic trend. Previous empirical analyses focused primarily on the time series properties of commodity prices alone (e.g. early work by Smith 1979 on aggregate mineral prices) with mixed evidence for the presence of stochastic trends and breaks (Berck and Roberts, 1995; Ahrens and Sharma 1997; Lee, List, and Strazicich 2006). Given the uncertainty around the time series properties of the data at hand, estimating and testing using (2) can be informative about the presence of a trend (or drift) irrespective of whether the individual time series are stochastically or deterministically trending. Beyond the existing literature, our analysis of individual commodities further controls for the possible presence of outliers (e.g. due to measurement errors). For reserves-to-production ratios, observations for the period 1980-87 had to be excluded because of consistent structural reporting issues.[6] For reserves-to-production ratio models, we therefore formally control for this missing time period by including indicator variables for each omitted year, allowing us to estimate models using the full sample without having to in-fill the missing years – see equation 2A. below. We include individual dummy variables for missing observations (captured by $\delta_{i,t}$ below in equation 2A), thereby removing their influence:

[6] The reserve base rather than reserves were reported by the MCS for the first time in 1980 which led, in subsequent years, to consistent reporting errors. From 1988 onwards, reserves and reserve base are reported side by side.

$$\Delta y_{i,t} = \beta_{i,t} + \sum_{t=1}^{T} 1_{t\in(1980:1987)}\delta_{i,t} + u_{i,t} \qquad (2A).$$

Thus, our main results for reserves-to-production ratios are based on (2A), while estimates for production and prices – which do not face the same measurement inconsistencies – are based on equation (2).

We initially analyse the presence of trends in prices, reserves-to-production, as well as production on a commodity-by-commodity basis using two approaches. First, we test for the presence of overall trends over the full sample by estimating equation (2) and (2A) not allowing $\beta_{i,t}$ (the linear trend or drift term in levels in) to vary over time ($\beta_{i,t} = \beta_i \, \forall \, t$). We estimate (2) and (2A) using the outlier-robust Impulse Indicator Saturation estimator (IIS, see Hendry et al. 2008; Johansen and Nielsen 2016) to control for potential outlying observations due to measurement errors and data inconsistencies. We assess the sensitivity of our results to the methods employed by repeating the analysis using conventional OLS estimates as well as an-established MM estimator (Yohai 1987, Koller and Stahel 2011) shown to be highly robust when applied to non-stationary (such as stochastically trending) time series in the presence of outliers (Maddala and Yin 1997).

Second, we estimate model (2) and (2A) allowing $\beta_{i,t}$ to vary over time for each commodity. We allow for step-shift changes in $\beta_{i,t}$ in equation (2) and (2A) for $\Delta y_{i,t}$ which correspond to a change in the trend in the level of $y_{i,t}$ in (1). The time-varying estimates of $\beta_{i,t}$ are obtained here using step-indicator saturation (SIS – Castle et al. 2015, Pretis et al. 2018) to detect structural breaks while controlling for potential outliers. Relative to existing studies detecting structural breaks and gradual transitions in commodity prices (e.g. Harvey et al 2010; Cuddington et al. 2014), we assess production as well as reserves-to-production ratios, since trends in prices alone are not sufficient to establish resource exhaustion. Break detection has been used extensively to identify changes in growth rates and trends in time series (Hansen 2001, Perron 2006). The robust break detection procedures (SIS, IIS) have been employed in a wide set of applications, ranging from detecting variation in the diffusion of innovation in medical practice (Walker et al. 2019), to test the accuracy of economic forecasts (Ericsson 2017), to study hurricane damages (Martinez 2020), to identify volcanic eruptions in temperature reconstructions (Schneider et al. 2017), as well as to assess the performance of climate models (Pretis et al. 2015). While there are alternative structural break methods (such as the Perron-Yabu 2009 approach), here we rely on SIS due to its ability to detect multiple structural breaks without a minimum break length while simultaneously controlling for potential outlying observations (e.g. due to measurement errors). The target significance level p_α in IIS and SIS determines the expected false-positive rate (i.e. selecting at 1% we expect 1% of observations to be detected as a structural break even if there is no break – the asymptotic convergence of the false positive rate to the chosen level of significance in SIS is established in Nielsen and Qian 2018). Indicator saturation methods are applied here at a target significance level of 1% when testing for the presence of time-varying trends, and a loose level of 10% to control for outliers (such as measurement errors) when estimating time-invariant trend estimates. Using $p_\alpha = 1\%$ results in less than one spuriously detected break per commodity on average given the approximately 60 years of observations ($p_\alpha \times 60 < 1$).

Following the analysis on a commodity-by-commodity basis, we analyse the presence of trends in a joint panel model of commodities. We test whether panel models of prices, reserve-to-production ratios, and production can each be pooled into models with common intercepts in first differences (capturing common trends or drifts in levels). We test the pool-ability of time-invariant trend coefficients ($\beta_i \neq \beta \ \forall \ i$) in equation (2) and (2A) using F- and Lagrange-Multiplier tests (Honda 1985, King and Wu 1997). Results and discussion based on further alternative model specifications – including allowing for persistence in $y_{i,t}$, estimating model (1) in levels with a deterministic trend and no long-run impact of shocks, and using a panel GMM estimator are reported in the Appendix.

4. Results and Discussion

Our results show that there is little evidence of near-term exhaustion of commodities. Reserves-to-production ratios and prices appear stable over time: outlier-robust estimates of trends are not statistically different from zero for nearly all commodities under analysis (see Figures 3, 4, and 5). Despite production having increased over time (Figures 2 & 5), reserves have been increasing to suggest a stable reserve-to-production ratio with a median of 50 years, which may reflect the planning horizon of extraction and discovery of new extractible reserves. Estimating trend-stationary models (1) of reserves to production ratios (while also controlling for missing observations in the 1980s similar to 2A) suggests more significant negative trend breaks, but these estimated linear trends are highly unstable throughout the sample and across commodities and mostly not statistically different from zero when controlling for persistence in the time series (see Appendix).

Expanding the analysis into panel to assess whether patterns are common across commodities, results show that prices and reserves-to-production ratios can each be pooled across commodities and do not exhibit statistically significant trends (though point estimates are positive and negative respectively), while production exhibits a statistically significant common positive trend (Figure 5 panel b, and Appendix). These results are robust to varying the time period of analysis as well as specifying dynamic panels (where the autoregressive lags found not to be statistically different from zero in most models – see Appendix).

Both the individual and pooled results indicate that the overall trend in prices is not different from zero for most commodities (except for Thallium for which, however, reserves-to-production have been stable[7] and for which the overall production value is low, ranking 46th out of the 48 minerals considered here). Similarly, reserves-to-production ratios do not exhibit negative trends for all but two mineral commodities in our dataset. The two commodities with negative trend estimates in reserves-to-production ratios are iron ore and soda ash, for which the falling ratios (driven by increased production) are countered by rising prices over the last 10 years of the sample – see Appendix.

While some of the available time series are short (less than 30 years), the absence of significant trends is not driven by a lack of power of the statistical approach. In fact, our results are able to identify that production of most minerals exhibits a statistically significant positive trend, and thus has been increasing over time. Combined with trendless prices and reserves-to-production ratios for all but two commodities, reserves are increasing over time. In summary, we can conclude that there is no strong evidence that we are running out of these key mineral commodities.

[7] Thallium prices increased in the early 1990s due to US domestic production shutting down (Bureau of Mines, 1993). Globally production volume has been comparatively low and production has been decreasing in the 2000s (Figure 2, bottom and U.S. Geological Survey, Mineral Commodity Summaries, January 2020).

Figure 3: Trend-coefficient estimates in log reserves-to-production ratios using OLS (left), outlier-robust MM and IIS over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right). The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.

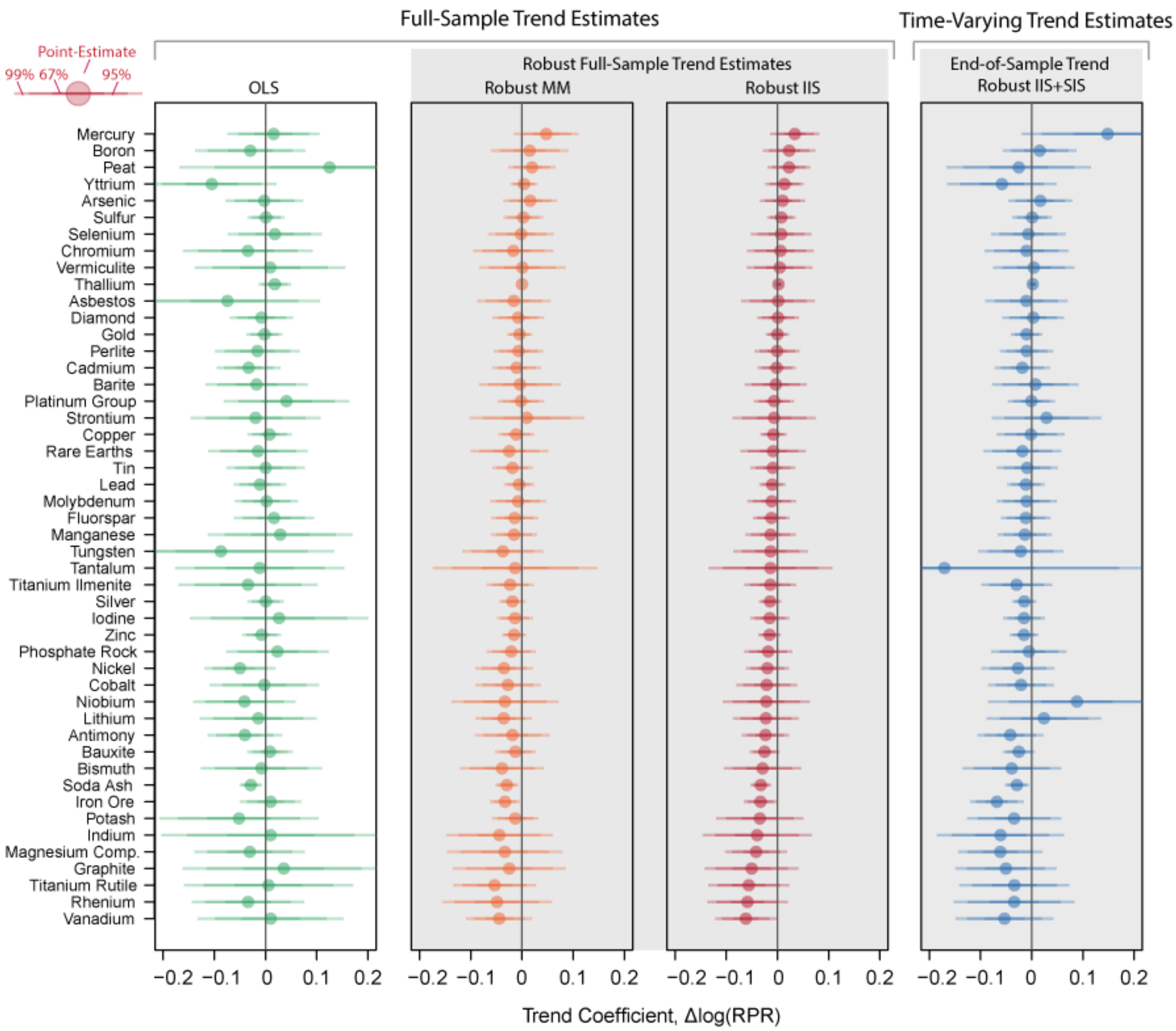


Figure 4: Trend-coefficient estimates in log prices using OLS (left), outlier-robust MM and IIS over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right). The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.

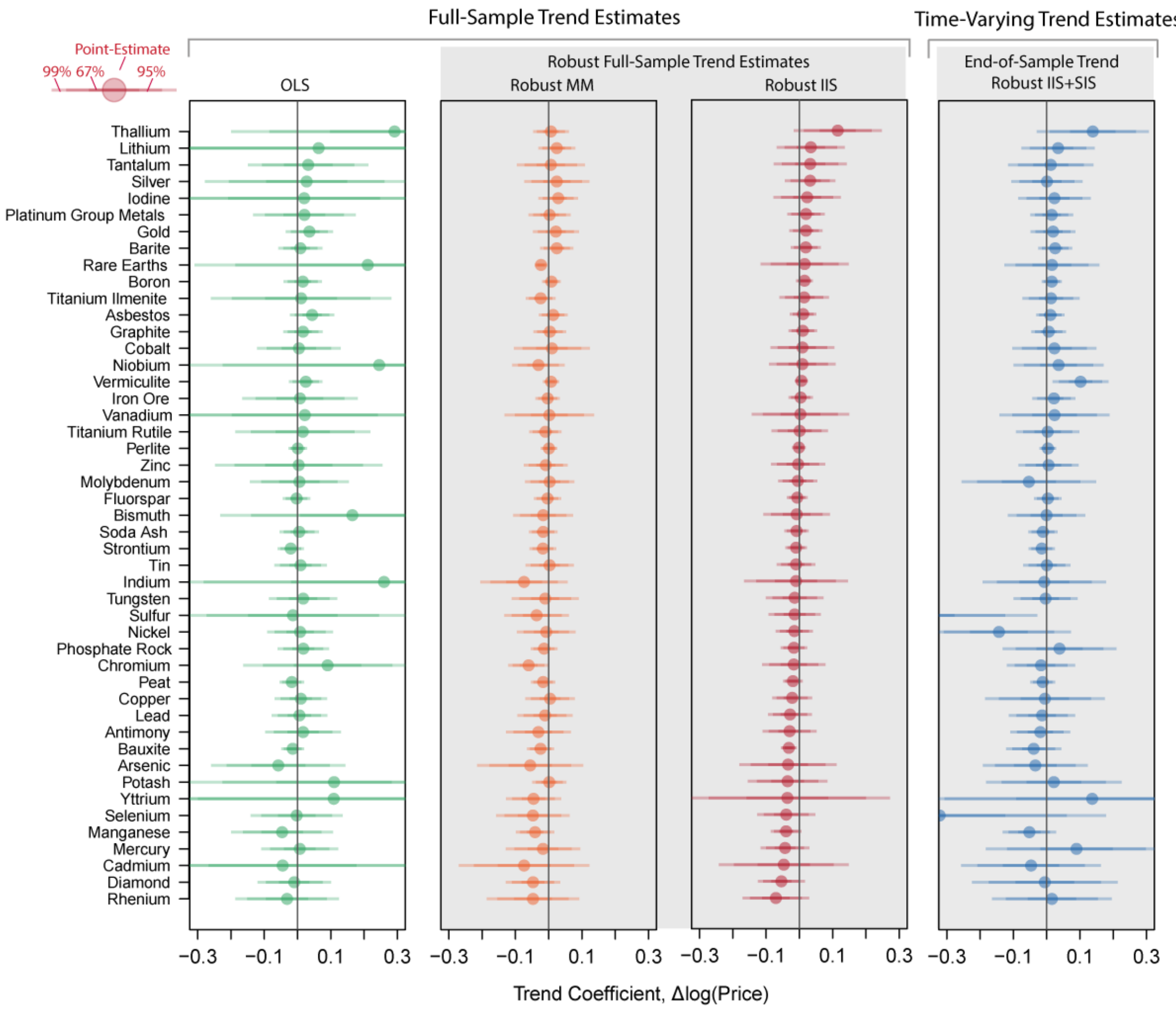
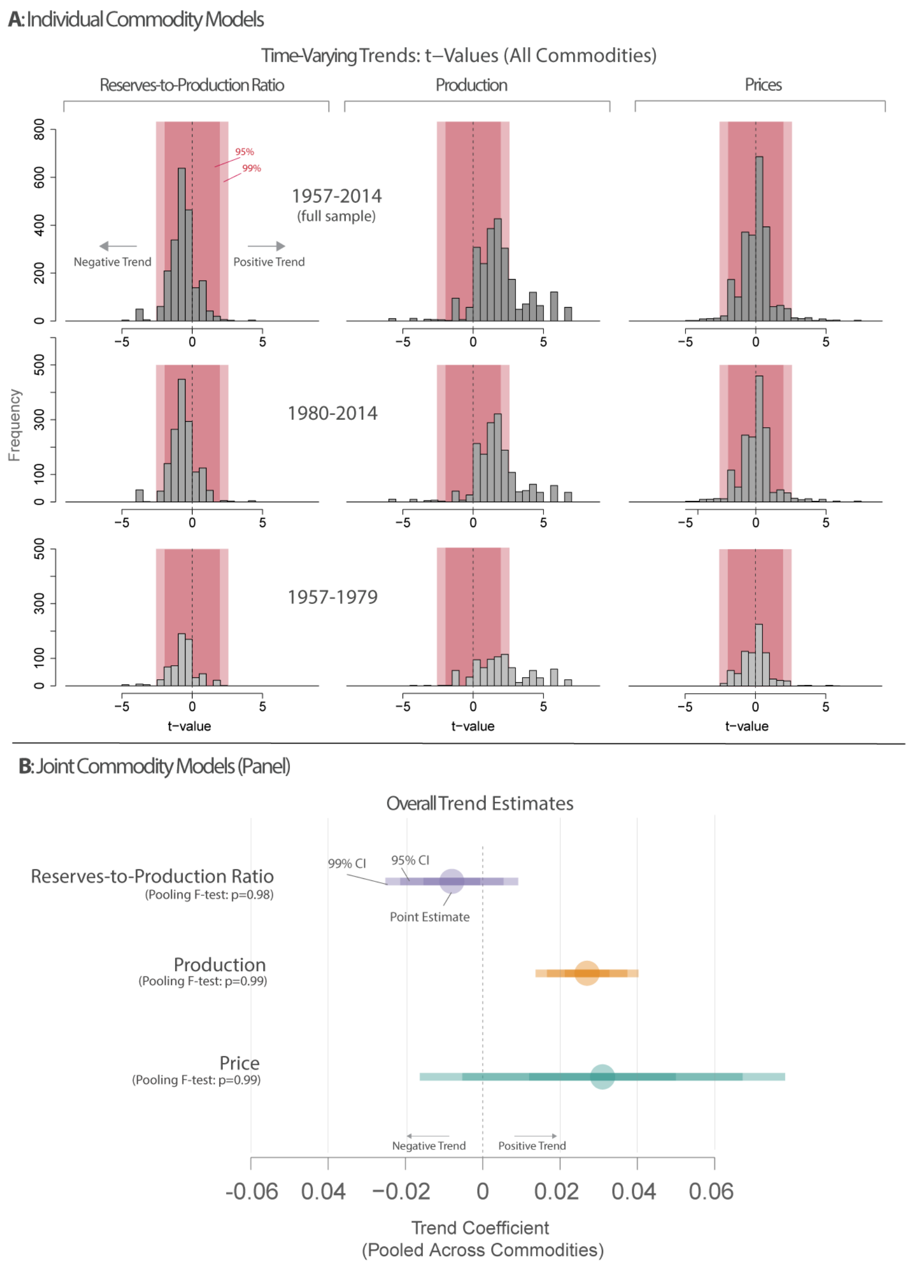


Figure 5: Panel A: Time-varying trends in log reserves-to-production ratios (left column), log production (middle column), and log prices (right column) across all commodities (modelled individually) and time periods. Panels show the distribution of t-values for significance tests of the time-varying intercept in first differences (trend in levels) for the full sample (top row), 1980-2014 (middle), and 1957-1979 (bottom). Critical values of the t-statistics are shown for 5% and 1% as dark and light red-shaded respectively. Bars falling outside the shaded critical regions indicate significant trends. Production has increased over time, while reserves-to-production ratios and prices have remained predominantly stable.

Panel B: Estimated common trend in log reserves-to-production ratios (purple), log production (orange), and log prices (green) using pooled panel estimates in first differences. Pooling F-tests show that commodities can be pooled sharing a common trend which is not statistically different from zero for reserves-to-production ratios (pooling p = 0.98) and prices (pooling p = 0.99) , and positive for production (pooling p = 0.99) .



5. Conclusion

The finding that we are unlikely to be running out of key mineral commodities does not imply that there could not be short-term resource shortages, spikes in prices, or politically-related constraints. For instance, as we transition to a zero-carbon economy, short-run pressures on key resources, such as cobalt, have been much discussed (EC 2017). Overall though, past fears about mineral exhaustion have not been realised and there is no indication in the data of future longer-term availability concerns. Over the last 50 years, market prices and other features of the commodities industry has ensured long-term availability of key minerals.

Our results do not imply that an ever-expanding materials-intensive model of economic growth is desirable, nor that we would want to mine all available minerals, such as those in the deep sea (Hoagland et al. 2010). There is vast evidence of the environmentally damaging consequences of mineral extraction and consumption, in contrast to the lack of evidence found here for concerns that such minerals might be exhausted. Policy attention should instead focus upon the degradation of renewable natural capital (such as the climate system, forests, fisheries, and biodiverse ecosystems) where adequate, scarcity-reflecting prices do not exist, and where environmental limits are more dangerous.

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Appendix

Appendix A provides additional details on the estimation methods. Appendix B provides a more detailed assessment of iron ore and soda ash, Appendix C-E provides additional estimation results for reserves-to-production ratios, production, and prices, and Appendix F lists all commodities under analysis ranked by their production value.

A. Additional Details on Estimation Methods

We test for the presence of trends using commodity-specific models as well as by modelling commodities jointly. We test for overall time trends as well as time-varying trends by estimating model (2) and (2A) for each commodity and variable of interest (detailed results on production and prices are reported in Appendix C-E). We then model commodities jointly using fixed effects panel models to test whether commodities can be pooled into a common model. We repeat the analyses controlling for autoregressive dynamics and using trend stationary models as in equation (1) - these are reported in the Appendix C-E.

A.1: Commodity-Specific Models

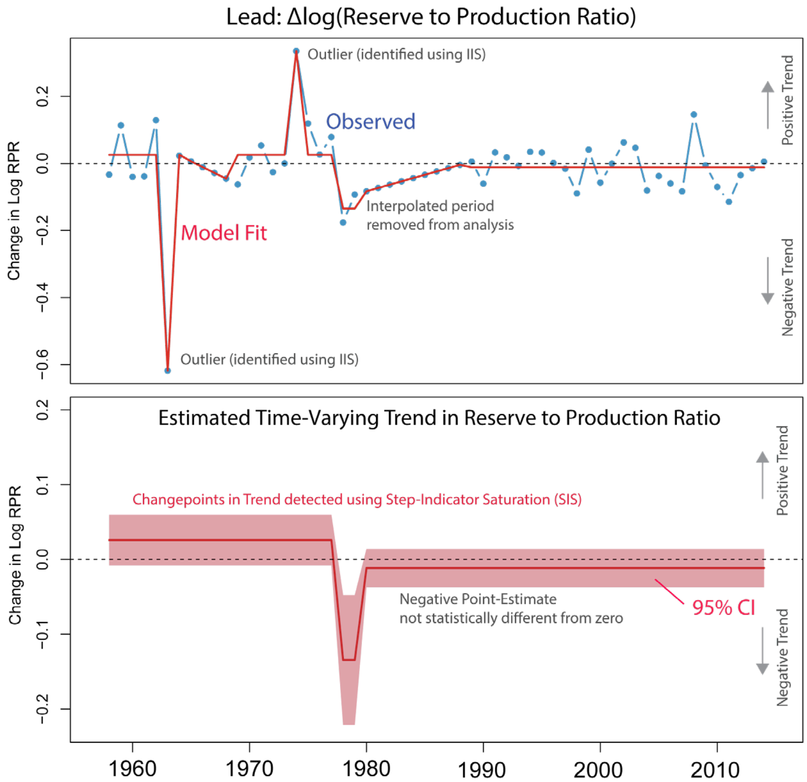
We estimate an overall trend (non-time varying) over the entire available sample ($\beta_{i,t} = \beta_i \ \forall \ i$) for each commodity i using OLS, robust IIS (Hendry, Johansen, and Santos 2008, Johansen and Nielsen 2016) at a loose level of p_α=0.1 significance to remove extreme observations, and a robust MM estimator (Yohai 1987, Koller and Stahel 2011). Robust regression using the MM estimator is implemented using the *robustbase* package in the statistical software environment *R* (Maechler et al. 2015). Indicator saturation methods are applied using the package *gets* (Pretis et al., 2018) in *R* at a significance level of 1% (allowing for a 1% false positive rate of detection) when testing for the presence of time-varying trends, and a loose level of 10% to control for outliers (such as measurement errors) when estimating time-invariant trend estimates. Impulses (i.e. outliers) in (2) account for outlying observations and can also identify level shifts in $y_{i,t}$.

For reserves-to-production ratios, observations for the period 1980-87 had to be excluded because of consistent structural issues: the reserve base rather than the reserves were reported by the MCS for the first time in 1980 which led, in subsequent years, to consistent reporting errors. From 1988 onwards, reserves and reserve base are reported side by side. For our reserves-to-production ratio models, we formally control for this missing time period by including indicator variables for each omitted year, allowing us to estimate models using the full sample without having to in-fill the missing years – see equation 2A. Estimates from (2A) are shown as the main results for reserves-to-production ratios reported in Figures 3-5. Production and price time series do not face the same measurement inconsistencies.

A 1.1: Time-Varying Trends in Individual Commodities

We use step-indicator saturation (SIS) to detect changes in the trend coefficient $\beta_{i,t}$ in equation (2) (and (A.2) for RPR) at a significance level of 1% (p_α=0.01).An illustration of the method is given in Figure A1 for the mineral *Lead*. The top panel shows the first difference of the reserves-to-production ratio, the lower panel shows the estimated coefficient path of $\beta_{i,t}$ – the value of the intercept over time with shifts detected using SIS. A positive value of $\beta_{i,t}$ implies a positive trend in the level. An approximate 95% confidence interval on the intercept term is given by the dotted-lines. Outlying observations are removed using IIS and are not counted towards the intercept (i.e., trend coefficient in levels). As can be seen, there are changes in the trends of reserves-to-production ratio, however, the trend coefficients are close to indistinguishable from zero when taking uncertainties into account. Repeating this analysis for every single commodity in the dataset, we then plot the distribution of trend coefficients across time across all commodities in Figure 5 (panel A). The last trend coefficient for each commodity determined using SIS is plotted in Figure 3 (right panel) for reserves-to-production ratios and Figure 4 (right panel) for prices.

Figure A.1: Demonstration of the Methods: detecting (time-varying) trends by analysing the intercept in first differences in log RPRs of Lead.



A.2 Modelling Commodities Jointly - Panel Models

We estimate fixed effects regressions of commodities jointly (A.2.1) and test the model against a pooled regression assuming a common intercept (trend in levels) (A.2.2):

$$\Delta y_{i,t} = \beta_i + \mathrm{u}_{i,t} \qquad \text{(A.2.1)}$$

$$\Delta y_{i,t} = \beta + \mathrm{u}_{i,t} \qquad \text{(A.2.2)}$$

For RPRs, as in the commodity-specific models we include dummy variables for the period of measurement inconsistencies:

$$\Delta y_{i,t} = \beta_i + \sum_{t=1}^{T} 1_{t\in(1980:1987)}\delta_{i,t} + \mathrm{u}_{i,t} \qquad \text{(A.2.1a)}$$

$$\Delta y_{i,t} = \beta + \sum_{t=1}^{T} 1_{t\in(1980:1987)}\delta_{i,t} + \mathrm{u}_{i,t} \qquad \text{(A.2.2b)}$$

We test the pool-ability of the series by considering the significance of individual fixed-effects (resource-specific intercepts capturing linear trends in levels) using the Honda (1985)/King and Wu (1997) LM tests, as well as a simple pooling F-test using the *plm* package (Croissant and Millo, 2008) in *R*. Estimation results for reserves-to-production ratios (using equation (A.2.2b)), as well as production and prices (using equation (A.2.2)) are shown in Figure 5, with full results provided in Appendix C-E. Additional results using dynamic panel methods (e.g. GMM to address concerns about biases in dynamic models, see Arellano and Bond, 1991; Nickell, 1981) are also discussed in Appendix C-E.

B. Detailed Assessment of Iron Ore and Soda Ash

The statistical analysis presented in Figure 3 in the main text finds a significant negative trend in reserves-to-production ratios of iron ore and soda ash (highlighted here in Figure B.2). This is driven by increased production (Figure B.3), and is countered by increasing prices over the end of the sample (Figure B.4).

Figure B.2: Reserves-to-production ratios (Figure 1) highlighting iron ore (purple) and soda ash (green) over 1957-2014. Observations over the early 1980s are shown as interpolated values, though interpolated observations are not used in the statistical analysis of the presence of trends.

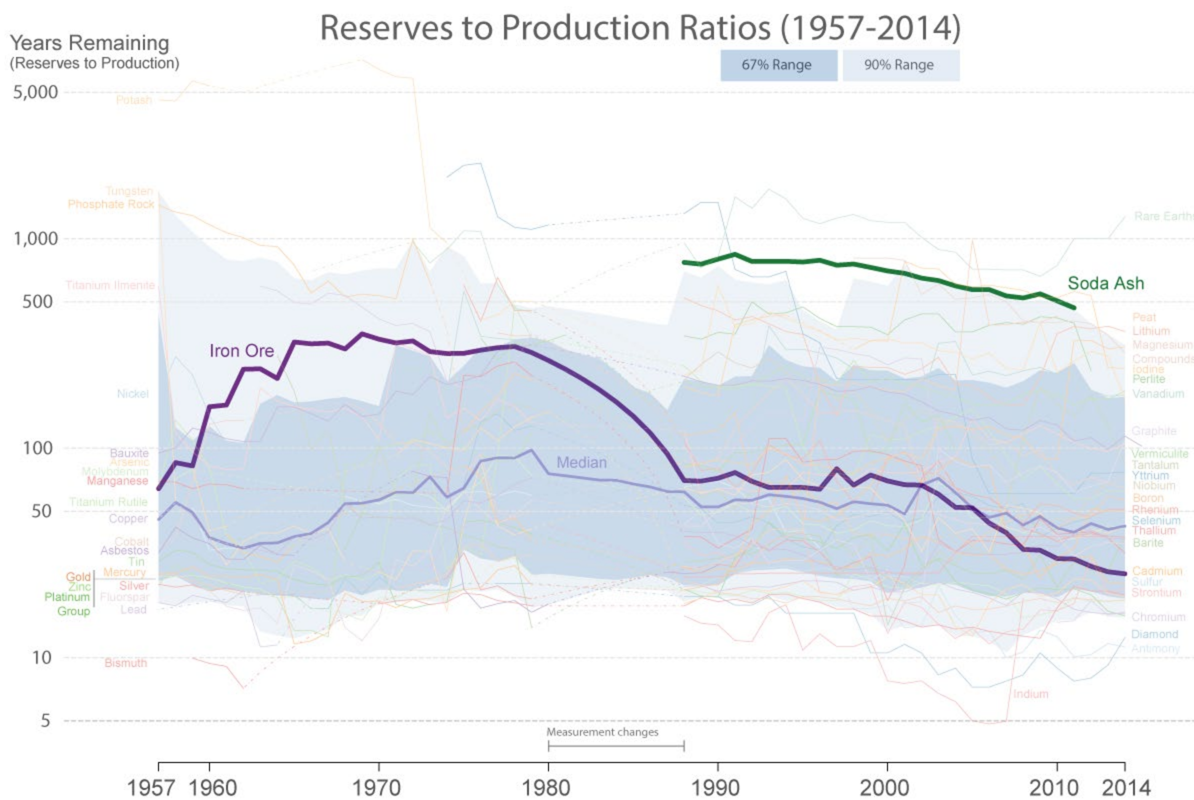


Figure B.3: Production index (Figure 1) highlighting iron ore (purple) and soda ash (green) over 1957-2014.

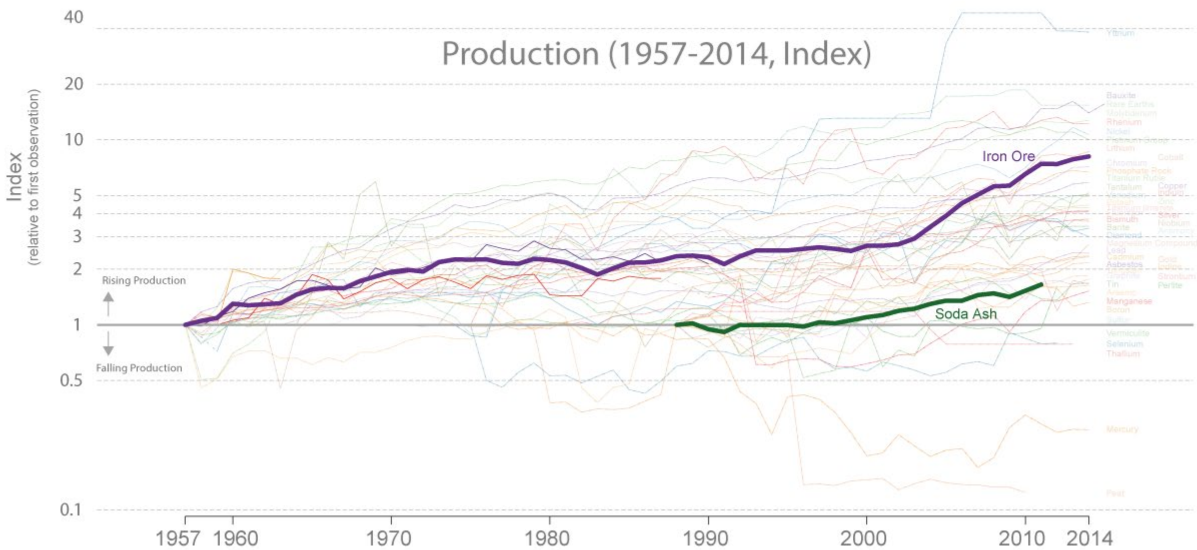
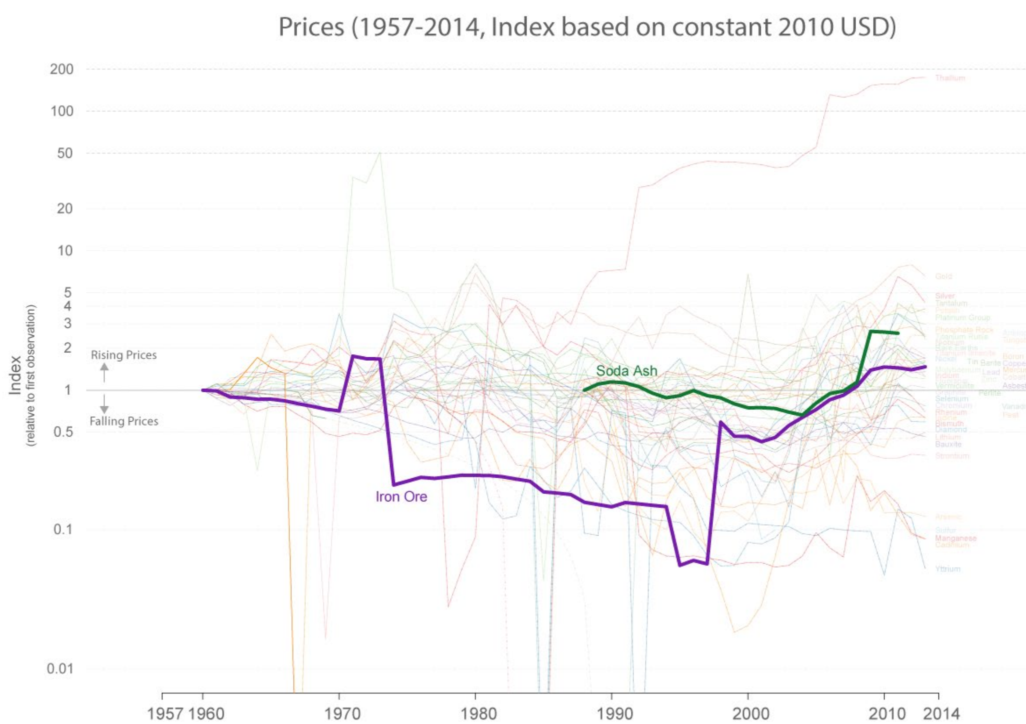


Figure B.4: Price index highlighting iron ore (purple) and soda ash (green) over 1957-2014 in constant 2010 USD.



C. Additional Estimation Results on Reserves-to-Production Ratios

C1.1 Modelling Commodities Jointly - Panel Estimation Results

We estimate (A.2.1a) and (A.2.2b) for Δlog(RPR), pooled estimation results for (A.2.2b) are shown in Figure 5 in the main text and Table S1. For the static log model the common-intercept estimate is small and negative at -0.008 (se=0.006) and not statistically different from zero. Testing pool-ability using F- and Lagrange-Multiplier tests, suggests that a common intercept is not rejected (p=0.98). The change in the log of reserves-to-production ratios of the 48 commodities can be modelled jointly with a common intercept with a negative point estimate which is not statistically different from zero. Results for dynamic panel model estimates including an autoregressive lag as in (C.2.3):

$$\Delta y_{i,t} = \beta + \rho \Delta y_{i,t-1} + \sum_{t=1}^{T} 1_{t \in (1980:1987)} \delta_{i,t} + \mathrm{u}_{i,t} \tag{C.2.3}$$

are shown in Table S1 (right columns). The overall results are not sensitive to the inclusion of autoregressive lags. The autoregressive lag term is not statistically different from zero, and pool-ability of commodities around an insignificant common trend is not rejected. These results are robust to estimating the dynamic model using the Arellano-Bond (1991) GMM estimator to address concerns about potential biases in dynamic panels (Nickell 1981). Estimating a dynamic panel using GMM, the estimated common trend (intercept in first differences) is given by -0.003 with a standard error of 0.006 (and resulting p-value of 0.57). Thus, there is no statistically significant common trend in reserves to production ratios. Further, when using GMM, the autoregressive lag is not statistically different from zero (p=0.47) supporting the analysis as a static panel.

Table C1 Panel Results	Dependent Variable: $\mathbf{\Delta \log(\mathit{RPR})_{\mathit{i,t}}}$	
	Static, (A.2.1b)	Dynamic, (C.2.3)
Trend, β (intercept in first differences)	-0.008 (0.0063)	-0.006 (0.006)
$\Delta y_{i,t-1}$	-	-0.001 (0.025)
Honda/King & Wu Test for Poolability	-2.032 [p=0.979]	-2.039 [p=0.979]
Pooling F-Test	F=0.588 [p=0.98]	F=0.66 [p=0.96]
Observations	2151	2055
	Standard errors in parentheses (), *** p < 0.001, ** p < 0.01, * p<0.05	

C1.2 Estimation Results when controlling for Autoregressive Dynamics in the Reserves-to-Production Ratios

Here we report the results of testing the presence of trends in RPRs when controlling for autocorrelation through the inclusion of an autoregressive lag term in the estimated models given here in C1.2.1:

$$\Delta y_{i,t} = \beta_{i,t} + \rho \Delta y_{i,t-1} + \sum_{t=1}^{T} 1_{t \in (1980:1987)} \delta_{i,t} + \mathrm{u}_{i,t} \quad \text{(C1.2.1)}$$

C1.2.1 Individual Commodity Results When Controlling for Autoregressive Dynamics

Figures C1.2.1.1 and C1.2.1.2 show the distribution of trend coefficients (intercept in first differences) when controlling for autoregressive lags. Results on the absence of trends reported in the main text are robust to the inclusion of autoregressive lags.

Figure C1.2.1.1: Time-varying intercepts (trends) in log reserves-to-production ratios across all commodities and different time periods when controlling for autoregressive lags. Right panels show the distribution of t-values for significance tests of the intercept in differences. Critical values of the test are shown for 5% and 1% as dark and light red-shaded respectively.

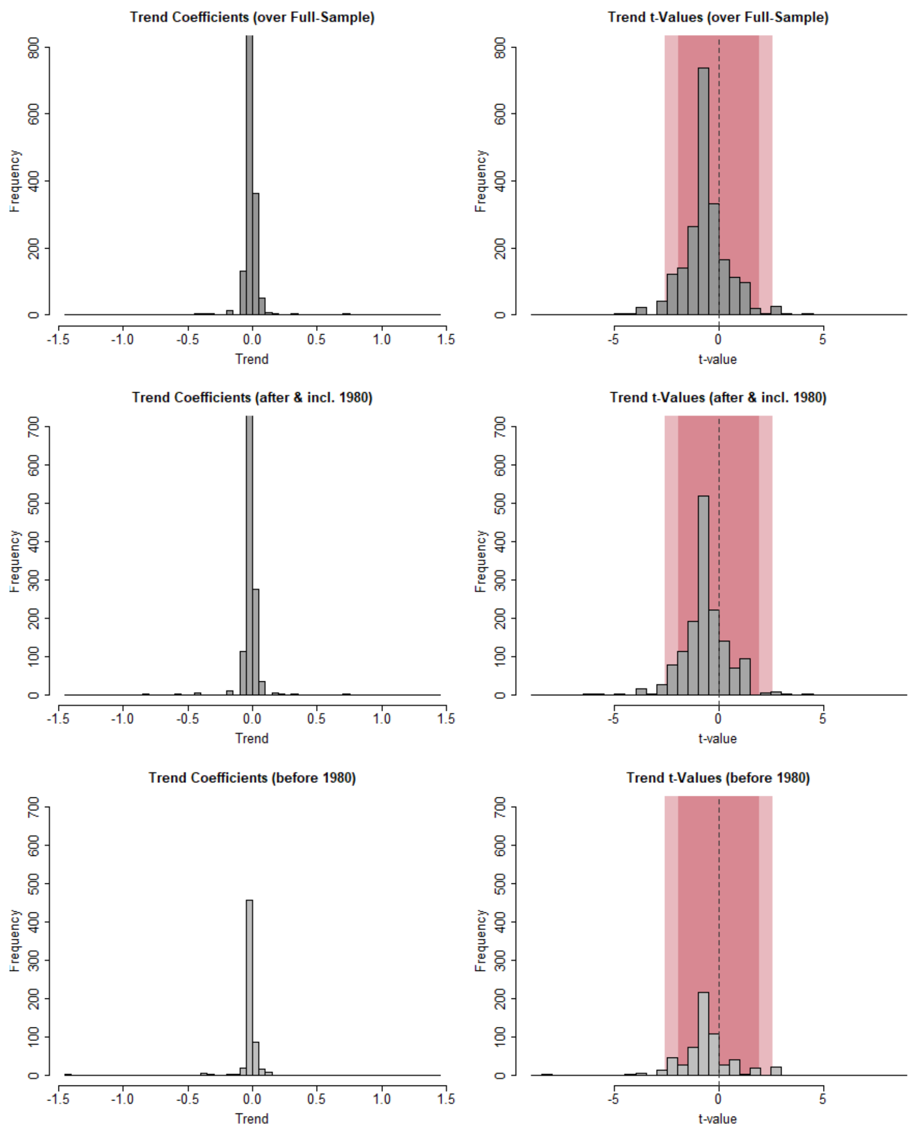
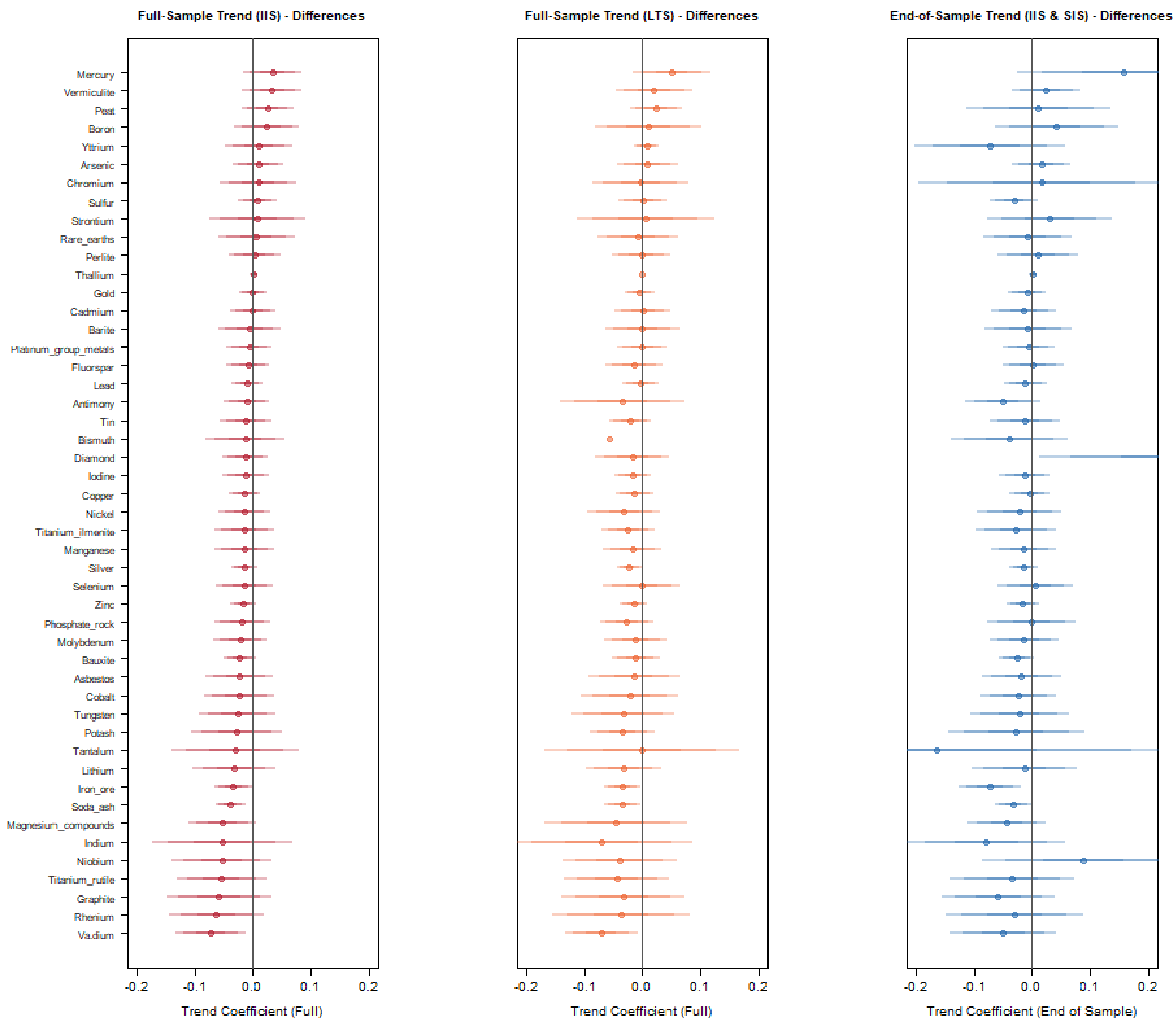


Figure C1.2.1.2: Trend-coefficient estimates in log reserves-to-production ratios using IIS over the full sample (left), the robust MM estimator over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right) when controlling for autoregressive lags. The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.



C1.3 Analysing Commodities Using a Trend-Stationary Model

When modelling commodities individually using a trend stationary model (equation (1) in the main text) results show that trends are highly unstable over the sample (Figure C1.3.1, and Figure C1.3.2 when controlling for autoregressive lags). Robust trend-coefficients over the full sample are predominantly negative (Figure C1.3.3) but not statistically different from zero when controlling for autoregressive lags (Figure C1.3.4).

Figure C1.3.1: Time-varying trends in log reserves-to-production ratios across all commodities and different time periods. Right panels show the distribution of t-values for significance tests of the intercept in differences. Critical values of the test are shown for 5% and 1% as dark and light red-shaded respectively.

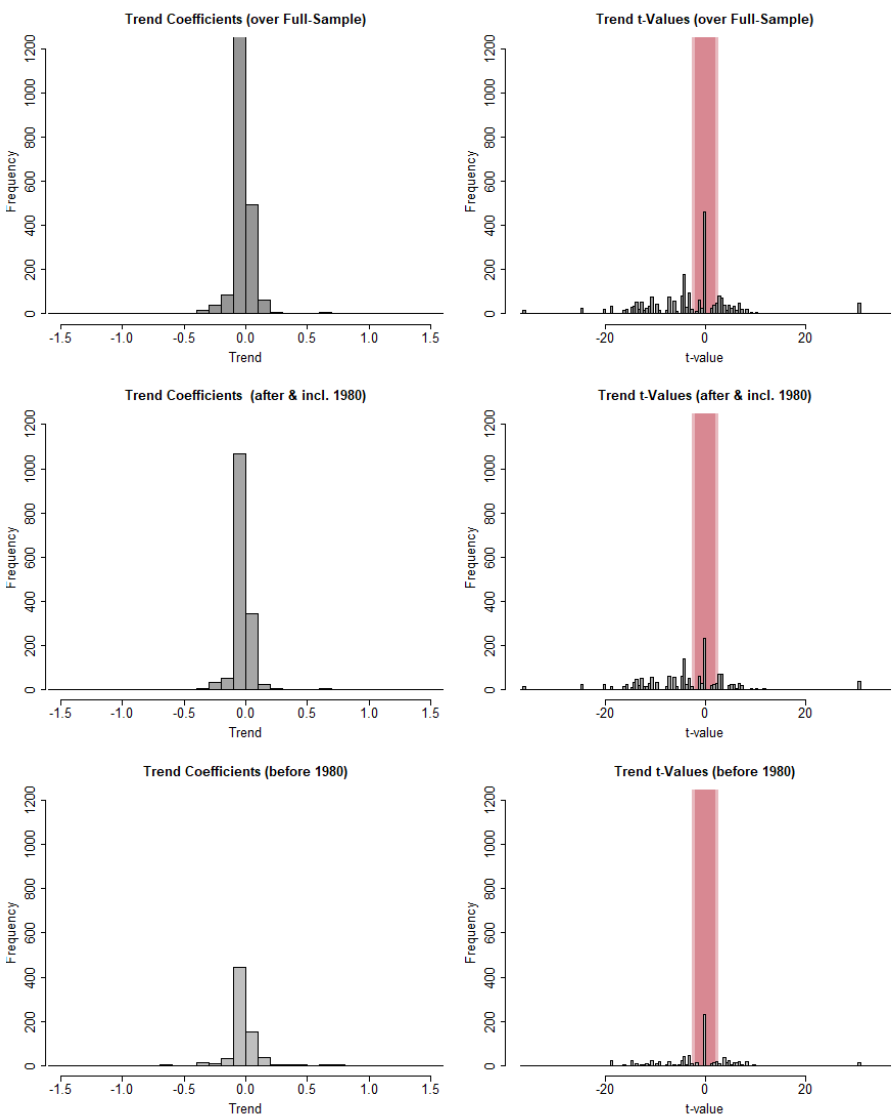


Figure C1.3.2: Time-varying trends in log reserves-to-production ratios across all commodities and different time periods when controlling for autoregressive lags. Right panels show the distribution of t-values for significance tests of the intercept in differences. Critical values of the test are shown for 5% and 1% as dark and light red-shaded respectively.

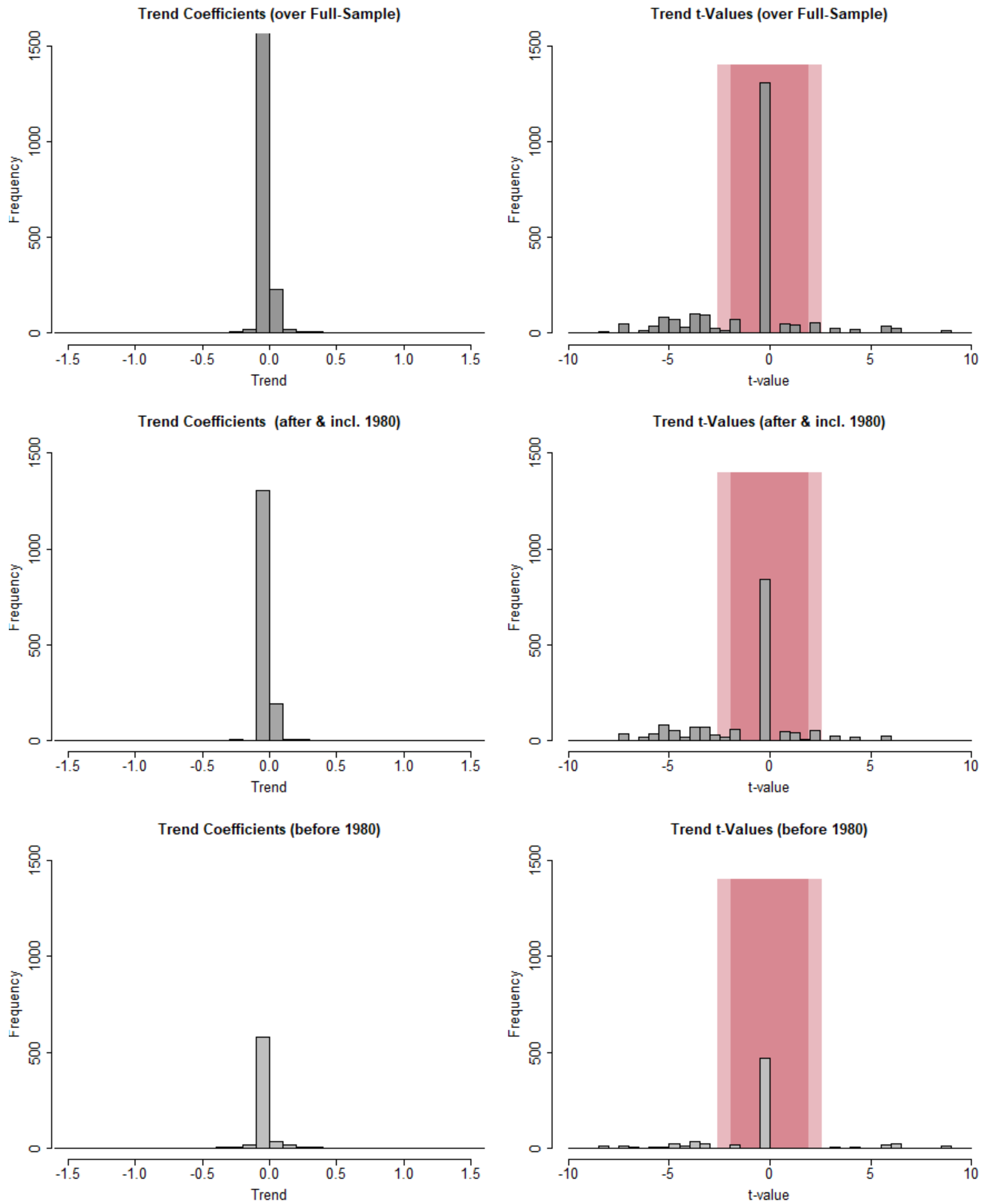


Figure C1.3.3: Trend-coefficient estimates in log reserves-to-production ratios using IIS over the full sample (left), the robust MM estimator over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right). The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.

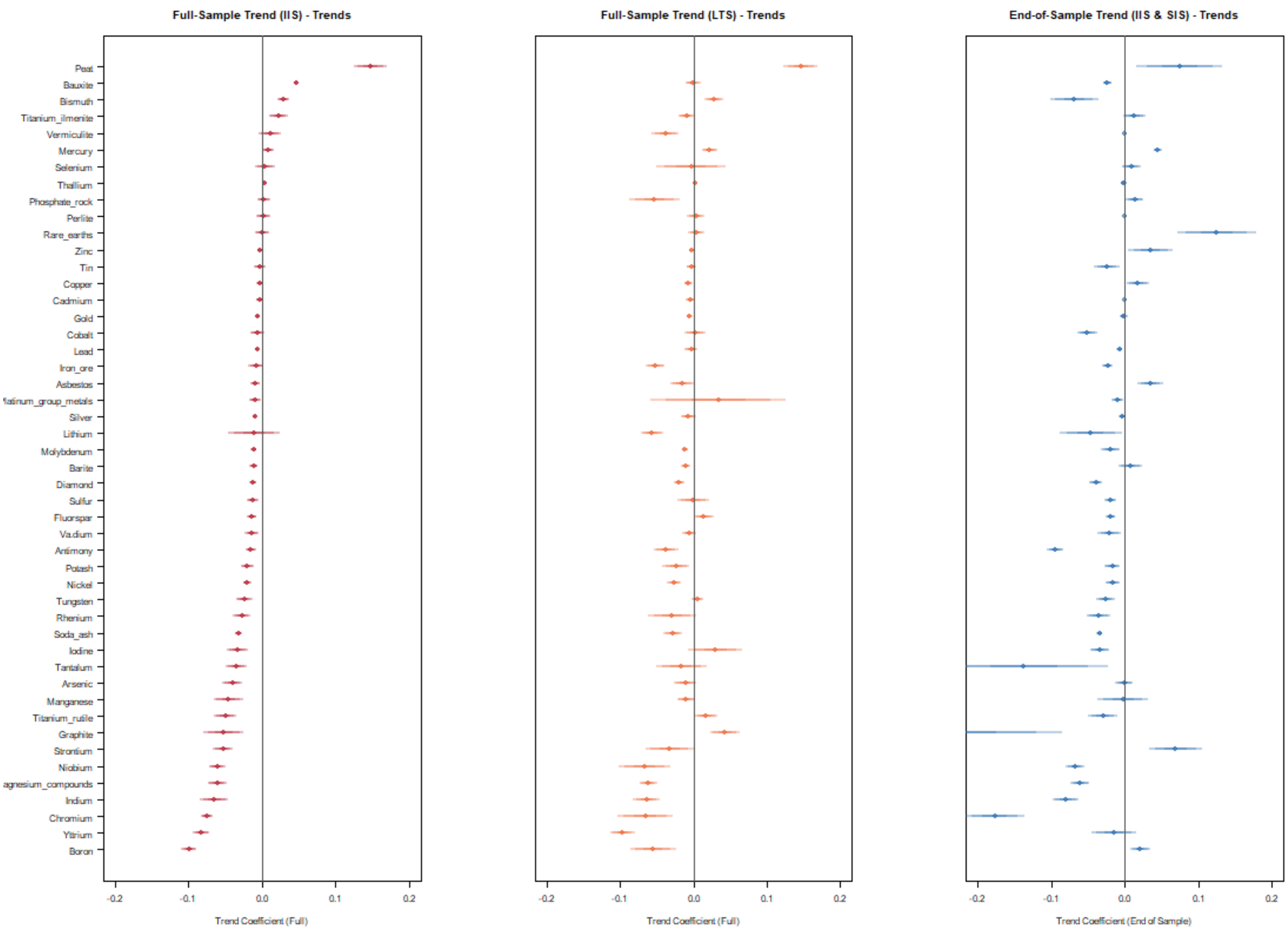
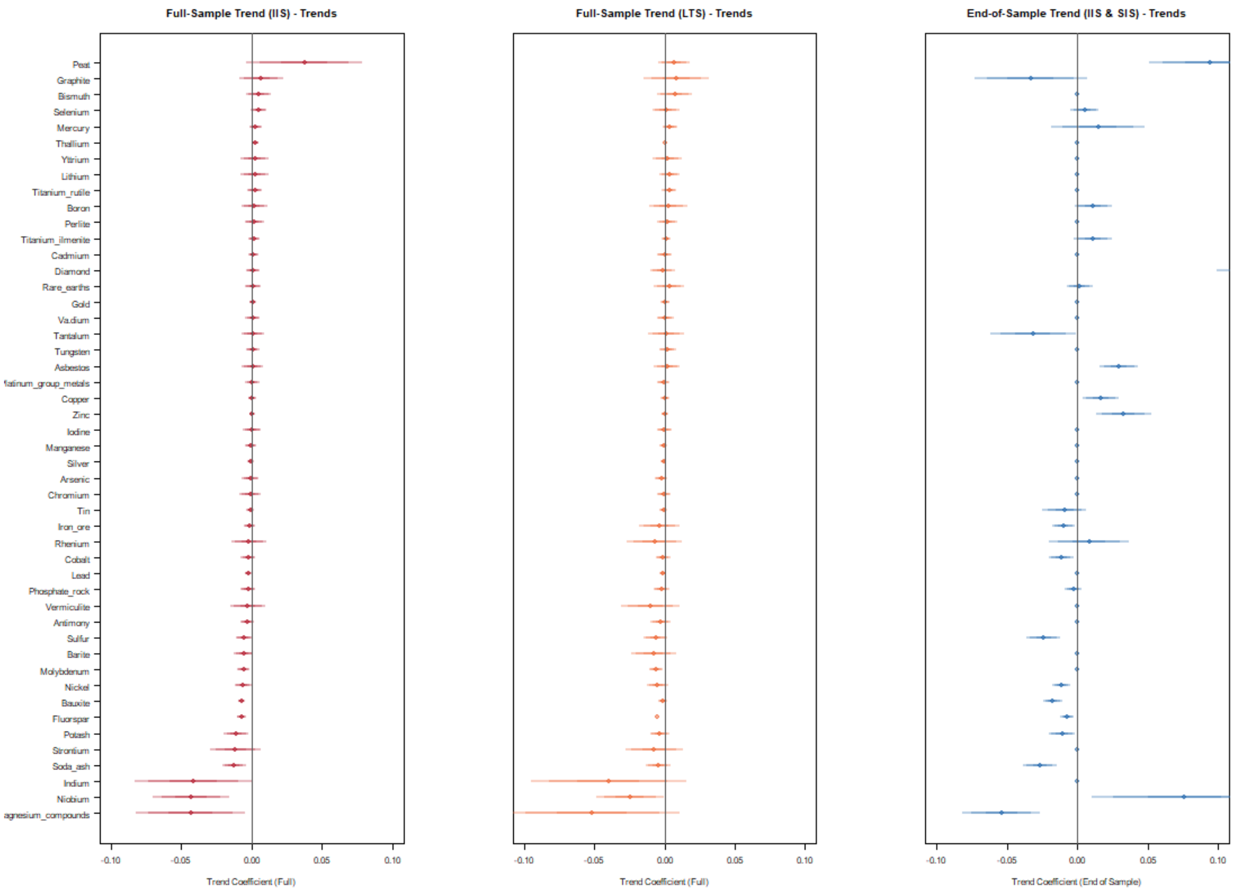


Figure C1.3.4: Trend-coefficient estimates in log reserves-to-production ratios using IIS over the full sample (left), the robust MM estimator over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right) when controlling for autoregressive lags. The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.



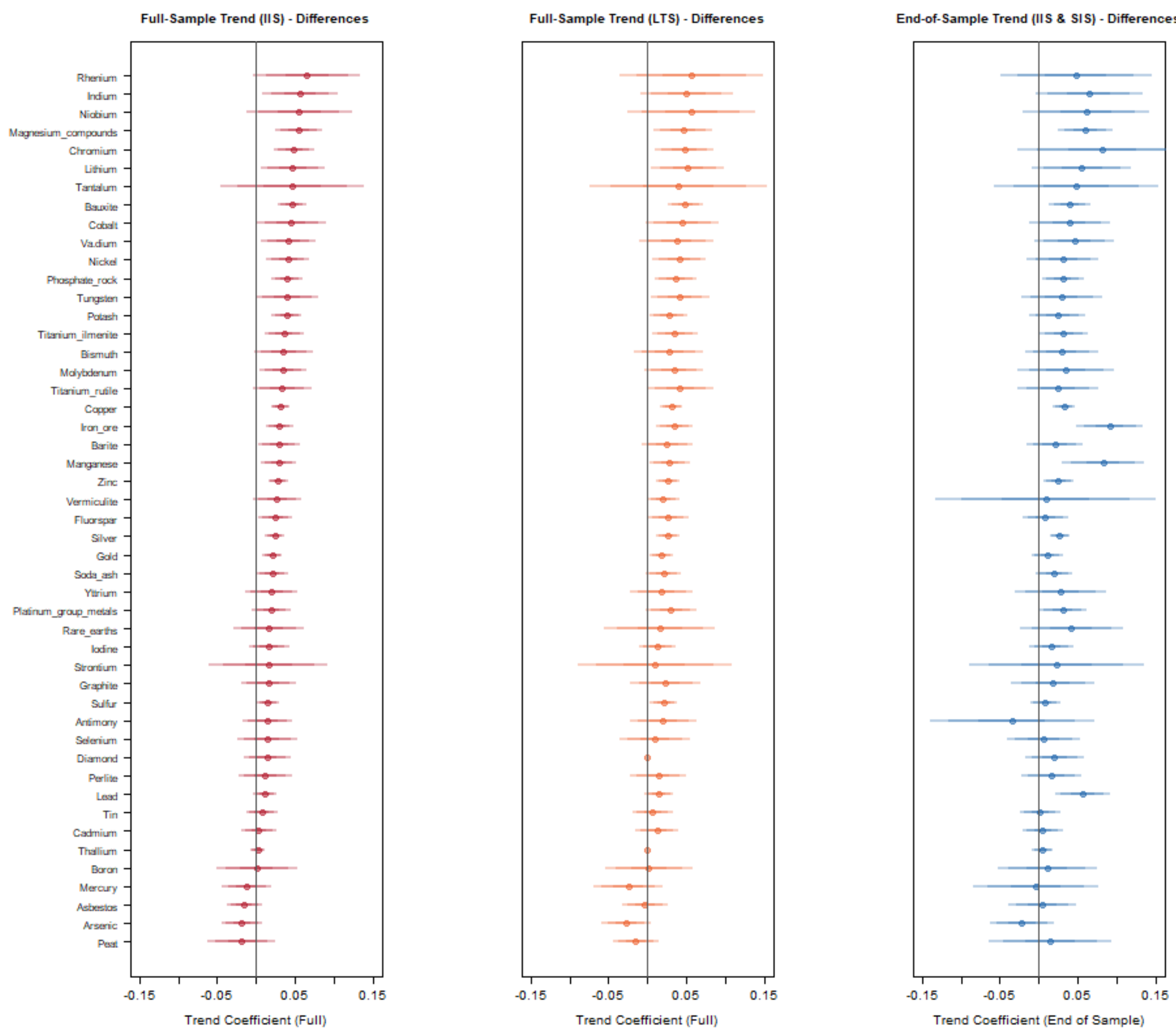
D. Analysing Production

We repeat the above tests for the presence of trends using production data (Figure 2, bottom panel). Data inconsistencies during the 1980s only affect reserves, thus no missing observations of production have to be modelled using dummy variables. Modelling production of commodities individually in first differences (as in equation (2)) shows that production has significantly increased over time for most commodities (Figure D2.1). Pooling tests in a panel of production do not reject the null hypothesis that resources can be pooled and modelled jointly with a significant positive trend in production over time (see Figure 5 in the main text and Table D1).

As is the case for reserved to production ratios, the dynamic panel results for production are robust to using the Arellano-Bond (1991) GMM estimator. Estimating a dynamic panel of production using GMM, the estimated common trend (intercept in first differences) is 0.032 with a standard error of 0.007 (and resulting p-value of <0.001). Thus, there is evidence of a statistically significant positive common trend in production. When using GMM, the autoregressive lag is not statistically different from zero (p=0.19) supporting the analysis as a static panel.

Table D1 Panel Results	Dependent Variable: $\boldsymbol{\Delta \log(Production)_{i,t}}$	
	Static, (A.2.1)	Dynamic, (A.2.1 with AR lag)
Trend, β (intercept in first differences)	0.027 (0.0048)***	0.032 (0.004)***
$\Delta y_{i,t-1}$	-	-0.044 (0.020)*
Honda/ King & Wu Test for Poolability	-2.908 [p=0.99]	2.022 [p=0.022]
Pooling F-Test	F=0.43 [p=0.99]	F=1.47 [p=0.02]
Observations	2520	2424
	Standard errors in parentheses (), *** p < 0.001, ** p < 0.01, * p<0.05	

Figure D2.1 Trend-coefficient estimates in log production using IIS over the full sample (left), the robust MM estimator over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right). The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.



E. Analysing Prices

We repeat the above tests for the presence of trends using data on commodity prices shown in constant 2010 US dollars per metric ton in Figure 1. Prices are inflation-adjusted using the GDP deflator (OECD, 2019). Data inconsistencies only affect reserves, thus no missing price observations have to be modelled using dummy variables. Modelling prices of commodities individually in first differences (as in equation (2)) shows that most prices have not significantly increased over time (Figure E3.1). Results of a panel analysis of poolability of prices are reported in Table E1 (and Figure 5 in the main text) showing that while the point-estimates are positive, they are not statistically different from zero. Changes in prices have been reasonably stable over time and can be pooled using a common intercept (trend in levels) that is not statistically different from zero for the static and dynamic models (at the 1% level).

Table E1 Panel Results	Dependent Variable: **Δlog(Prices in constant 2010 dollars)**$_{i,t}$	
	Static, (A.2.1)	Dynamic, (A.2.1 with AR lag)
Trend, β (intercept in first differences)	0.024 (0.018)	0.036 (0.017)*
$\Delta y_{i,t-1}$	-	-0.327 (0.020)***
Honda/King & Wu Test for Poolability	-3.81 [p=0.99]	-2.71 [p=0.99]
Pooling F-Test	F=0.255 [p=0.99]	F=0.52 [p=0.99]
Observations	2342	2248
	Standard errors in parentheses (), *** p < 0.001, ** p < 0.01, * p<0.05	

Figure E3.1 Trend-coefficient estimates in log prices using IIS over the full sample (left), the robust MM estimator over the full sample (middle), and time-varying linear trends using SIS at the end of the sample (right). The 95% and 99% confidence intervals around the trend estimates are shown as shaded bars. Commodities are ordered by the magnitude of their trend coefficient from the IIS analysis.

F. Production Value of Commodities

Table F1 ranks the resources by their 20-year average value (from 1994 to 2014) given by production multiplied by the constant (2010 dollars) price per tonne.

Table F1: Relative value of resources

	Resource	**20-year Avg. Production (tonnes) times Price (million constant 2010 USD)**
1	Iron Ore	73,071
2	Gold	54,872
3	Copper	53,753
4	Nickel	18,800
5	Zinc	16,366
6	Platinum Group Metals	10,173
7	Potash	8,756
8	Silver	7,553
9	Phosphate Rock	7,491
10	Soda Ash	4,719
11	Lead	4,624
12	Molybdenum	4,121
13	Bauxite	4,048
14	Sulfur	3,257
15	Tin	2,771
16	Asbestos	2,718
17	Peat	2,488
18	Cobalt	2,120
19	Chromium	1,679
20	Boron	1,567
21	Fluorspar	1,096
22	Graphite	713
23	Tungsten	689
24	Diamond	683
25	Antimony	608
26	Vanadium	578
27	Titanium Ilmenite	528
28	Iodine	522
29	Yttrium	500
30	Titanium Rutile	364
31	Barite	354
32	Niobium	293
33	Manganese	255
34	Indium	152
35	Arsenic	138
36	Cadmium	100
37	Tantalum	84
38	Rhenium	84
39	Vermiculite	83
40	Perlite	80
41	Lithium	77
42	Rare Earths	76
43	Bismuth	73
44	Selenium	66
45	Mercury	44
46	Thallium	26
47	Strontium	26
48	Magnesium Compounds	missing overlapping price/production information