Perez-Sebastian, Fidel; Raveh, Ohad; van der Ploeg, Frederick

Natural Resources, Technology Improvements, and Growth

Environmental and Resource Economics

Provided in Cooperation with:
Springer Nature

Suggested Citation: Perez-Sebastian, Fidel; Raveh, Ohad; van der Ploeg, Frederick (2025) : Natural Resources, Technology Improvements, and Growth, Environmental and Resource Economics, ISSN 1573-1502, Springer Netherlands, Dordrecht, Vol. 88, Iss. 8, pp. 2157-2199, https://doi.org/10.1007/s10640-025-01004-x

Environmental and Resource Economics (2025) 88:2157–2199
https://doi.org/10.1007/s10640-025-01004-x

Natural Resources, Technology Improvements, and Growth

Fidel Perez-Sebastian[1] · **Ohad Raveh**[2] · **Frederick van der Ploeg**[3,4,5,6]

Accepted: 7 May 2025 / Published online: 24 June 2025

Abstract
We study, analytically and empirically, how technological changes affect the nexus between resource abundance and economic growth. Our two-sector model indicates that capital-augmenting technological improvements can be contemporaneously contractionary in resource-rich economies, and expansionary elsewhere, due to differences in the size of the elasticity of substitution between labor and capital. In addition, such improvements yield relatively steeper expansionary patterns in resource-rich economies in the longer run. We test these predictions using a panel of U.S. states and counties. Our identification strategy rests on geographically-entrenched differences in resource endowments, and the adoption of plausibly exogenous technology shocks at the national level. Our core estimates corroborate our predictions. First, we document persistent differences in the elasticity of substitution between capital and labor across the natural-resource dimension. Second, we find that an increase in TFP is on impact contractionary in resource-rich states, but is non-contractionary (at worst) in resource-poor ones. Third, we illustrate that in the longer term a positive technology shock expands output and inputs in resource-rich economies relatively more strongly. Our results shed light on hitherto overlooked potential adverse effects of natural resource abundance.

Keywords Natural resource abundance · Technology shocks · Input elasticities

JEL classifications Q32 · E32 · O33

Fidel Perez-Sebastian, Ohad Raveh, and Frederick van der Ploeg contributed equally to this work.

Extended author information available on the last page of the article

1 Introduction

Understanding the nexus between natural resources and economic growth has been of perennial interest to economists and policy makers, especially in discussions of the resource curse. The literature so far has highlighted a host of potential transmission channels.[1] Little attention, however, has been given to the potential role of technological changes.[2] The latter represents a pivotal phenomenon with long-lasting implications for the economy. Nonetheless, the empirical literature still debates the size of the contemporaneous impacts.[3] This study examines how resource abundance interacts with technological changes to affect growth. We hypothesize, and demonstrate using U.S. data, that technology improvements induce a contemporaneously divergent outcome on growth in output and labor, across the natural resources dimension. Our results shed light on previously overlooked potential adverse effects of natural resource abundance, and offer one possible reconciliation for the ongoing debate over the opposing contemporaneous effects of TFP shocks on the economy.

The notion that the oil and gas sectors tend to be relatively intensive in capital and low-skilled labor has been documented in previous studies (e.g., Michaels et al. 2014). The well-documented capital-skill complementarity hypothesis (e.g., Krusell et al. 2000) then suggests that the elasticity of substitution between capital and labor (hereafter, the ESKL) should be relatively higher in resource-rich sectors. This prediction has been substantiated in a number of cross-sectional studies. [4] Moreover, Raveh (2020) illustrates that these features may translate to the macroeconomic level in economies with a dominant oil and gas sector, noting that resource-abundant economies are consistently more capital-intensive over a period of three decades. We hypothesize that this may similarly extend to the size of the ESKL, positing that it is persistently relatively higher in extractive industries.

Importantly, the relative size of the ESKL can be central to understanding the contemporaneous impact of technological changes on economic activity.[5] The intuition is simple: a positive technology shock increases the productivity of capital, but it also reduces the need for labor through factor substitution. To examine this analytically, we construct a two-sector (extractive and non-extractive) model of economic growth with capital adjustment costs, and economy-wide labor- and capital-augmenting technological change. The analytical results indicate that while labor-augmenting technological improvements are similarly expansionary in both sectors, the short- and long-term patterns may differ for capital-augmenting improvements. Specifically, a capital-augmenting technology shock increases the productivity of capital while substituting labor, thus giving rise to involuntary unemployment in the short-run due to capital adjustment costs. These costs result in a gradual conver-

[1] See, e.g., Allcott and Keniston (2018), Arezki et al. (2017), Armand et al. (2020), Brollo et al. (2013), Gylfason et al. (1999), James and Rivera (2022), Tornell and Lane (1999), Torvik (2002), and the references therein. Van der Ploeg (2011) and Venables (2016) provide syntheses of the literature.

[2] The literature unveils the potential endogeneity of TFP shocks and innovation to resource abundance (e.g., Kuralbayeva and Stefanski 2013). However, it overlooks the potential role of resource abundance in transmitting the effects of technological changes on the economy.

[3] While standard frictionless real business cycle models predict short-term expansionary effects, other canonical macro workhorse models predict the opposite (e.g., Chang and Hong 2006). This inconclusive evidence, along with the other related literature, is reviewed in more detail in the following section.

[4] See, e.g., Caballero et al. (1995), Young (2013).

[5] The notion that the ESKL parameter is central for understanding the impacts of technological changes dates back to Hicks (1932) and Satō (1975). For a more recent analysis, see Cantore et al. (2014).

gence back to full employment. Hence, in the short-term the impact is contractionary if the ESKL is sufficiently high; yet, in the long-term the magnitude of the expansion depends on the initial capital-intensity, thus pointing at the potential divergent outcome across resource-rich and -poor economies.

The model also serves to derive sector elasticities and capital- and labor-augmenting technology shocks over time using U.S. industry-level data. Our estimates reveal that extractive industries indeed exhibit consistently higher ESKL than non-extractive sectors, averaging around 0.79 compared to 0.55 for other sectors. The latter underpins our subsequent analysis, in which we empirically examine our main analytical predictions, using an extensive panel of U.S. states and counties, covering the period 1963–2015. Employing plausibly exogenous measures of national technology shocks—the purified U.S. TFP series of Basu et al. (2006) (henceforth, BFK)—and geologically determined cross-sectional state resource abundance from James (2015), we exploit geographic and temporal variation to identify the differential effects of technology improvements across resource intensities. Our empirical strategy hinges on interacting state-level resource endowments with national technology shocks, facilitating causal identification through geographic and temporal exogeneity.[6]

Our empirical analysis provides robust support for our analytical predictions. We find that positive national TFP shocks, most notably capital-augmenting ones, have a contemporaneously contractionary effect on output and employment in resource-rich states, driven by labor market impacts, whereas it is expansionary or at worst neutral in resource-poor states. Quantitatively, our baseline estimates suggest that a standard deviation increase in TFP decreases the average output of resource-rich states by approximately 0.1% relative to resource-poor states in the short term. Nonetheless, our estimates also show that two to five years ahead, positive TFP shocks lead to relatively stronger expansions of output and inputs in resource-rich states, aligning with our model's predictions. Finally, we show that these patterns are robust to a battery of robustness tests that consider different treatments, sample restrictions, specifications, and controls.

Section 2 reviews related literature and places our contributions within it. Section 3 explains analytically how resource abundance interact with technology shocks to affect growth. Section 4 presents the data, empirical findings, and robustness tests. Section 5 concludes.

2 Related Literature

Our contributions relate to three strands of literature. First, natural resource abundance can be a blessing as well as a curse.[7] A central aspect is the potential negative impact of resource abundance on productivity and innovation. Among the various channels proposed, natural resource wealth may depress factor productivity (e.g., Gylfason et al. 1999; Krugman 1987; Sachs and Warner 2001; Torvik 2001; Van Wijnbergen 1984), lower human capital (e.g., Bhattacharyya and Hodler 2010; Gylfason 2001; Stijns 2006), and induce special-

[6] This methodology is reminiscent of that adopted in other studies that have also examined the heterogeneous local effects of aggregate shocks, by testing the impact of their interaction, including Liu and Williams (2019), Perez-Sebastian et al. (2019), and Raveh (2020), among others.

[7] See the surveys in Van der Ploeg (2011) and Venables (2016) for effects at the national level, and Van der Ploeg and Poelhekke (2016) for effects at the local level.

ization that crowds out innovation and entrepreneurship (e.g., Kuralbayeva and Stefanski 2013; Michaels 2011; Torvik 2002). In contrast, our analytical and empirical setups consider (national) technology shocks that are exogenous to resource abundance at the level of individual states, and advance a novel hypothesis concerning the interaction of resource abundance and technological shocks and its potential impact on short- and long-term growth. We find that improvements in technology are contractionary on impact primarily in resource-rich areas, and are more expansionary, relative to the remaining areas, in the longer term. Our results shed light on hitherto overlooked negative impacts of natural resource abundance.

Second, dating back to the seminal contributions of Kydland and Prescott (1982) and Gali (1999), the question of whether technology improvements are contractionary or expansionary has taken a central role in the macroeconomic literature. While standard frictionless real business cycle (RBC) models predict that technology improvements are expansionary in the short-term, sticky-price models predict the opposite.[8] The related empirical literature is also inconclusive. For instance, in their seminal work BFK show that technology improvements are contractionary on impact due to decreases in input use, most notably labor. However, Christiano et al. (2004) demonstrate that their correction of the BFK technology measure yields contemporaneously expansionary effects, focusing on labor. More recently, Cantore et al. (2014) highlight that the factor-augmenting nature of shocks and the ESKL are critical in determining the impact of technology shocks on the labor input in both RBC and sticky-price frameworks.

We contribute to this literature by analyzing the role of natural resources in the transmission of these shocks. Specifically, our analysis offers one potential reconciliation for the opposing views based on the underlying persistent differences in the ESKL between extractive and non-extractive industries. We observe that the short-term impacts of technology improvements are contractionary primarily in resource-rich areas, where extractive industries hold a significant share of the economy, but are mostly expansionary elsewhere. We show that these patterns arise using BFK's measure, time frame, and methodology, and that they are applicable also when implementing corrections like those undertaken in Christiano et al. (2004). Further, consistent with previous studies, we show that in the long-term positive technology shocks are expansionary across all areas, albeit more so in resource-rich regions.

Third, there is no shortage of studies that provide estimates for the aggregate ESKL (e.g., Doraszelski and Jaumandreu 2013; Klump et al. 2007; Raval 2019). The evidence summarized in Chirinko (2008) point at estimates well below one. Industry-level estimates point at similar magnitudes, albeit with some heterogeneity across sectors (Balistreri et al. 2003; Caballero et al. 1995; Young 2013). Notably, these studies estimate the substitution elasticity in the extractive industry to be amongst the highest, and even *the* highest under various specifications, relative to the other industries.[9]

Since estimates pertain to specific samples, we estimate the time series for the ESKL in the oil sector within our sample's time frame and compare it to the time series for the aver-

[8] However, non-standard RBC models can also generate a negative correlation between hours worked and technology shocks. See, for example, Francis and Ramey (2005).

[9] For example, Young (2013) employs the equation system approach proposed by León-Ledesma et al. (2010) and finds a larger average value of this elasticity across the mining and quarrying activities (0.72) than across the rest of sectors (0.63). Furthermore, he estimates that the largest elasticity among the former activities is for the oil and gas extraction industry (0.87).

age elasticities of the rest of the economy. We achieve this by employing U.S. industry data to compute the elasticity parameter directly from our analytical framework, which incorporates CES production functions and non-neutral productivity shocks—both essential for the estimation of elasticities (Antras 2004). We obtain estimates consistent with those reported in previous literature: the estimates are below one, and the ESKL in the extractive industry is significantly and consistently higher than the corresponding elasticity for the average of the remaining economy.

3 Technology Shocks in a Two-Sector Economy

Here, we analyze the implications of cross-sector differences in resource intensities (tied to differences in the ESKL) for the short- and long-term impacts of productivity shocks. We begin by presenting the basic elements of the model. Next, the predictions are organized into propositions, with the proofs relegated to Appendix A. The section also derives the testable predictions that the subsequent empirical section will focus on. Finally, we conclude by performing a structural estimation of the sectoral ESKL and the bias of technology shocks, and by discussing the implications for resource-rich and resource-poor economies.

3.1 The Environment

Consider an economy with two production sectors: extractive (e) and non-extractive (m). The non-extractive product is the numeraire. The economy is inhabited by a constant population of N individuals that are endowed with one unit of labor. Each period t, individuals supply their labor unit inelastically in exchange for a salary (w_t). We suppose that capital and output markets are open to the rest of the world. The labor market is closed and labour is internationally immobile. We have a small open economy. Therefore, if p_i represents the price of output in sector i, and R is the gross return to capital (i.e., the interest rate plus the depreciation rate), then $p_m = 1$, while the resource price p_e and R are constant and given on world markets.

Markets are perfectly competitive and firms maximize profits. In the short-run, firms in sector i, with $i \in \{e, m\}$, employ productive capital (k_{it}) and labor (n_{it}) at time t according to the following Leontief production function

$$y_{it} = \Omega_{it} \min \left\{ z_{kt} k_{it}, \omega_{it} z_{nt} n_{it} \right\}, \tag{1}$$

where y_{it} represents output in sector i at period t, z_{kt} and z_{nt} provide productivity levels specific to capital and labor, respectively, Ω_{it} is a productivity parameter specific to sector i, and ω_{it} represents the level of effective capital per unit of effective labor.[10]

New technologies bring labor-augmenting gains when z_{nt} rises, and capital-augmenting technical progress when z_{kt} rises. The new vintages also come with particular values of ω_{it} and Ω_{it}. These values result from the long-run, sector-specific ESKL (ε_i) not being equal to zero. Specifically, in the long-run, the production function takes the CES form

[10] We could include the stock of natural resources as an additional input in the production functions associated with the extractive activity. Our qualitative predictions would not be affected by this modification if natural resources enter the production function through a Cobb-Douglas form (see Appendix B).

$$y_{it} = \left[(z_{kt} k_{it})^{1-1/\varepsilon_i} + (z_{nt} n_{it})^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1}}. \tag{2}$$

We assume that the values of ω_{it} and Ω_{it} result from imposing the fixed input proportions dictated by the solution to the maximization problem faced by firms under the long-run production function given by Eq. (2).[11]

Finally, following Caballero (1994) and BFK, our framework features investment adjustment costs. In particular, the capital motion equation is given by

$$k_{it} = (1-\delta) k_{it-1} + x_{it}^{\phi}, \tag{3}$$

where x_{it} denotes investment, δ denotes the depreciation rate, k_{it-1} is the productive capital inherited from the previous period, and $\phi \in (0,1)$.[12]

3.2 Predictions

Our first proposition presents the values of ω_{it} and Ω_{it} that drive short-run output and shows how they depend on capital-augmenting productivity z_{kt}, but are determined by the long-run problem.

Proposition 1 *The optimal level of effective capital per unit of effective labor is*

$$\omega_{it} = \left[\left(\frac{z_{kt}}{R} \right)^{1-\varepsilon_m} - 1 \right]^{\varepsilon_i/(1-\varepsilon_m)}$$

and increases in z_{kt} and decreases in the user cost of capital. The vintage-specific parameter is

$$\Omega_{it} = \left[1 + \omega_{it}^{(1-\varepsilon_i)/\varepsilon_i} \right]^{\varepsilon_i/(\varepsilon_i - 1)}$$

and decreases in z_{kt}. Both ω_{it} and Ω_{it} are independent of z_{nt}

Proof. See Appendix A. □

[11] Appendix C analyzes a version of the model that includes skilled labor and accounts for sector-specific productivity shocks. The production function displays capital-, skilled-, and unskilled-biased productivity shocks, along with capital-skill complementarity within a CES-nested-in-CES specification. The main conclusion is that results similar to our main findings hold. More specifically, capital-biased and skilled-biased productivity shocks have positive effects on long-run ouptut, and these effects can be amplified by ε_e. However, this amplification is less likely when shocks originate from unskilled-biased productivity. Negative short-run effects on output are more likely to result from capital-biased than from skilled-biased productivity and, once again, can be amplified by ε_i. Importantly, unskilled-biased productivity shocks can never cause short-run output losses.

[12] For simplicity, the presence of investment adjustment costs in our model are captured through the parameter ϕ. Therefore, we follow a reduced-form approach. For more general forms of introducing investment adjustment costs in macroeconomic models, see Francis and Ramey (2005) for example.

Due to the constant input proportions dictated by ω_{it}, the difference between the short and long run lies in the total amount of labor used in production. In the short run, if the capital-labor ratio increases while capital grows slowly due to adjustment costs, the constant input proportions may imply that total labor demand falls short of total labor supply, thus leading to involuntary unemployment.[13] However, in the long run, capital accumulates until the economy reaches full employment. Therefore, given that labor moves towards the most productive sector and labor productivity increases in both production activities, technology shocks are always expansionary in the long run. Furthermore, while the impact of labor augmenting technology is independent of the ESKL, capital-augmenting technology shocks tend to generate stronger labor-productivity growth as the ESKL increases.

The following proposition summarizes the effects of technology shocks in the long run.

Proposition 2 *An increase in capital-augmenting productivity z_{kt} or in labor-augmenting productivity z_{nt} leads to an increase in labor productivity in both sectors. Furthermore, in the long run, which is characterized by full employment, an increase in z_{kt} or z_{nt} yields larger levels of output. Additionally, the change produced by labor-augmenting productivity z_{nt} is independent of the ESKL. If capital-augmenting productivity z_{kt} rises, the induced growth of labor productivity in the extractive activity increases with ε_e if $(z_{kt}/R)^{1-\varepsilon_m} > 2$ and $\varepsilon_m < 1$, or if z_{kt}/R is sufficiently close to 1 and either $\varepsilon_m > 1$ or both ε_e and ε_m are smaller than 1.*

Proof See Appendix A. □

A corollary to Proposition 2 is that, under the stated parameter restrictions, if $\varepsilon_e > \varepsilon_m$, the growth of labor productivity caused by an increase in z_{kt} will be larger in the extractive sector than in the non-extractive sector. This result suggests that economies in which the extractive activity contributes sufficiently more to total output will tend to grow more in the long run in response to an increase in z_{kt} if $\varepsilon_e > \varepsilon_m$. As mentioned previously, in the short run, since capital and labor enter the production function in fixed proportions and capital does not move to the new long-run equilibrium immediately, employment can be below N. Importantly, if the economy does not have full employment, the impact of a capital-augmenting technology shock can be contemporaneously contractionary.

The following proposition summarizes these short-run effects.

Proposition 3 *A positive labor-augmenting technology shock z_{nt} can never cause a fall in output. However, because optimal investment in capital decreases with ϕ, if ϕ is sufficiently low, a positive capital-augmenting technology shock z_{kt} can contemporaneously reduce output. In the non-extractive activity, this occurs if $\varepsilon_m > 1$, but if $\varepsilon_m < 1$, y_{mt} always increases with z_{kt}. In the extractive sector, sufficient conditions for y_{et} to fall with z_{kt} are $\varepsilon_e = \varepsilon_m > 1$, or $\varepsilon_m < \varepsilon_e < 1$ and z_{kt}/R is sufficiently close to 1.*

[13] In principle, individuals are willing to work at any wage because the labor supply is inelastic. However, $\omega_{it} \equiv \frac{z_{kt}k_{it}}{z_{nt}n_{it}}$ is fixed at its long-run value, as established by Proposition 1, which implies that labor demand equals $n_{it} = \frac{z_{kt}k_{it}}{z_{nt}\omega_{it}}$. Therefore, if ω_{et} or ω_{mt} have increased sufficiently, whereas k_{et} or k_{mt} grow relatively slowly, the sum $n_{et} + n_{mt}$ can be lower than N in the short run, where N denotes the full-employment level.

Proof. See Appendix A. □

To better understand Proposition 3, note that adjustment costs introduce diminishing returns to investment. Furthermore, for very low values of ϕ, these diminishing returns can be so strong that capital may experience only negligible increases. Thus, in the short run, if the increase in z_k causes a sufficiently large reduction of labor per unit of capital, and ϕ is sufficiently low, the fall in the labor demand due to the larger ω_i can dominate the positive effect of a higher z_k, resulting in a decrease in output.[14] Regarding the short-run effect of a change in z_n, recall that it neither affects ω_i nor Ω_i. So, a higher z_n only serves to increase the optimal stock of capital, and as a result, output cannot fall in the short run.

3.3 Testable Hypotheses

The analysis indicates that a capital-augmenting increase in productivity boosts output in the long-run but may reduce output in the short-run if the ESKL is larger in the extractive sector than in the non-extractive sector. This finding leads to two testable hypotheses. The first one is that a technology improvement in capital in a sector where it is easier to substitute labor for capital will lead to (1) higher output growth in the long-run, and (2) a smaller increase or even reduction of output in the short-run. The second testable prediction is that (3) a labor-augmenting improvement in productivity boosts output both in the short and in the long run.

Our strategy to test these hypotheses consists of two steps. We first estimate the ESKL and find that the ESKL is higher for the extractive than for the non-extractive sectors. Armed with this insight, we then proceed to test these hypotheses employing a sample of economies that differ in their degree of natural resource abundance.

3.4 Sectoral Elasticities of Substitution Between Labor and Capital

Our analysis thus points at a primary triggering primitive of the sign of technology-shock effects on the economy, namely cross-sectional differences in the ESKL. As noted earlier, there is already some cross-sectional evidence that supports this hypothesis (e.g., Young 2013).[15] We now explore the hypothesis that the ESKL is persistently higher in extractive industries.

For this, similar to Caselli and Coleman (Caselli et al. 2006), we first derive expressions from the model that allow recovering the productivity and elasticity parameters z_{kt}, z_{nt}, ε_e, and ε_m, and then estimate them using cross-industry U.S. data. We start from equation (2) and, for the estimation, allow R, w_t and ε_i to vary across time and sectors, while z_{kt}

[14] For example, the conditions stated in Proposition 3 for an increase in y_{mt} and a decrease in y_{et} as a consequence of an increase in z_{kt} are fulfilled for $\varepsilon_m = 0.6$, $\varepsilon_e = 0.8$, $z_{kt} = 0.5$, and $R = 0.2$. The values of ε_m and ε_e are the average estimates obtained in Sect. 3.4. The value of z_{kt} is the maximum estimate obtained in Sect. 3.5. Finally, $R = 0.2$ corresponds to the historical S&P 500 average return of 0.10(see, e.g., https://www.stern.nyu.edu/adamodar/pc/datasets/histretSP.xls.) minus a 0.02 average annual inflation rate calculated using data from Bureau of Labor Statistics for the U.S. consumer price index from 1998 to 2015, and an average depreciation rate of 0.12 calculated for the same period from Table 1 in Escribá-Pérez et al. (2023).

[15] Although we do not consider cross-sectoral differences in adjustment costs, empirical evidence indicates that adjustment costs in extractive industries are significantly higher than in other industries (e.g., Groth and Khan 2010), thus strengthening the suggested mechanism.

and z_{nt} vary across time but not across sectors. We employ U.S. industry-level data from the EUKLEMS dataset (O'Mahony and Timmer 2009), which covers the major 2-digit SIC industries for the period 1998–2015.[16] Sector e corresponds to the SIC classification of Mining and Quarrying, whereas sector m corresponds to a weighted, size-adjusted, average of the remaining industries. See Appendix D for the details of the estimation exercise.

For the estimation of the sectoral ESKL, we have assumed that input prices differ between sectors. However, this is inconsistent with the proposed model. As a result, any wage differentials between sectors not explained by the model could affect the estimated technology and, more notably, the elasticity parameters that potentially differ between sectors. Still, the estimated elasticities, shown in Fig. 1, fall within the range found in the literature (e.g., Chirinko 2008), which lends some support to our estimation results. Importantly, ε_m is consistently below ε_e in Figure 1 throughout the examined period, with average values of 0.55 and 0.79, respectively. This reinforces our hypothesis that the ESKL is persistently higher in extractive activities.

3.5 Estimates of Labor- and Capital-Augmenting Productivity Shocks

Figure 2 plots the estimated labor-augmenting and capital-augmenting shocks to productivity, z_{nt} and z_{kt}. There is some co-movement in the initial and later years, and divergence in other years. We will employ these common productivity shocks in our core analysis in an attempt to examine their separate impact on growth in output and inputs, along the lines suggested by our analytical predictions.

[16] This sample period is limited by data availability, but contained within the time interval examined in the posterior econometric analysis.

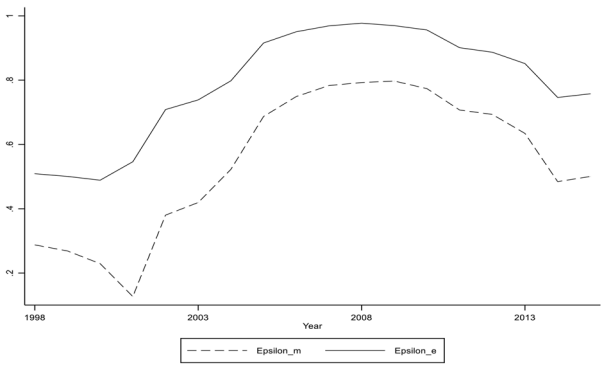

Fig. 1 Estimated elasticities of substitution between labor and capital are higher in mining and quarrying than in remaining sectors. The estimates were computed from U.S. industry data retrieved from the EUKLEMS dataset (O'Mahony and Timmer 2009) for the period 1998–2015. The resource industry e represents industry B in SIC classification (mining and quarrying), whereas industry m represents a weighted, size-adjusted, average of the remaining industries. The average ϵ_e(ϵ_m) over the whole period is 0.79 (0.55)

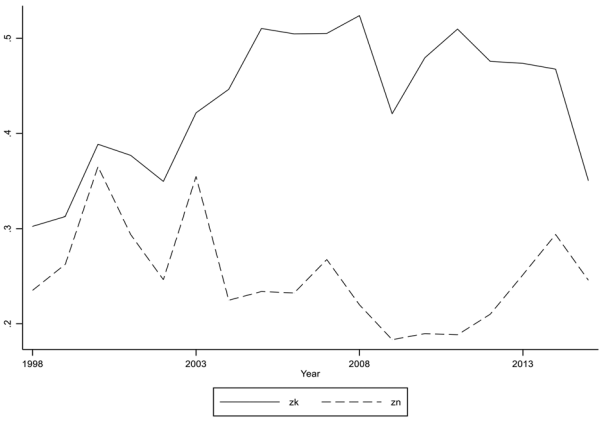

Fig. 2 Estimated common capital- and labor-augmenting productivity shocks. Computed from U.S. industry data retrieved from the EUKLEMS dataset (O'Mahony and Timmer 2009) for the period 1998–2015

3.6 Implications for Resource-Rich and Resource-Poor Economies

To help understand the main implications of our analysis for the resource-rich and resource-poor economies that will be used in the subsequent empirical exercise, we recall that the empirical evidence presented in Figure 1 suggests that $\varepsilon_e > \varepsilon_m$. Additionally, resource-rich economies typically exhibit a relatively large weight of the extractive sector e in gross domestic product, as empirically illustrated in the literature.[17] In resource-poor economies the dominant industries are the remaining sectors, which are represented by sector m in our model.

Our previous results suggest that in the case of resource-rich economies, total aggregate output can decline in the short-run and increase in the long-run as a response to capital-augmenting technical progress. However, in resource-poor economies, the same type of technology shock will increase total output, both in the short- and in the long-run. Labor-augmenting technology shocks, on the other hand, will have a positive effect on aggregate output regardless of the time horizon and the level of resource abundance. Furthermore, the long-run income-growth effect will be larger in resource-rich economies because they enjoy a larger aggregate ESKL.[18]

4 Empirical Analysis

Our analysis of Section 3 explains how the sign and extent of the contemporaneous and longer term impacts of technology shocks may depend on the degree of natural resource abundance. Here we test empirically the implied testable hypotheses. We do so by examining the heterogeneous effects of U.S. national TFP shocks on the output and inputs of individual U.S. states and examine how these depend on the degree of natural resource abundance.

[17] See, e.g., Van der Ploeg and Poelhekke (2016) for local and national case studies.

[18] Elasticity differences result in different capital intensities across sectors, due to the ESKL impact on the effective-input ratio ($\frac{z_k k_i}{z_n n_i}$). Empirical evidence for capital intensity differences across the natural-resource dimension are discussed in Sects. 1 and 2.

We initially focus on the contemporaneous effects, because they represent the main features of the divergent paths we aim to observe empirically. Later we also analyze the dynamic patterns. We first outline the data, and methodology. Then, we report the estimation results. Within the latter part, we begin by examining the role of the natural resources dimension within the BFK framework. Thereafter, we present the main results followed by robustness tests.

4.1 Data

We examine an annual-based panel of the 48 continental U.S. states over the period 1963–2015, limited by data coverage. We undertake an intra-U.S., cross-state perspective for several reasons.[19] First, while constituting a relatively homogeneous environment, U.S. states provide significant cross-state variation in the degree of resource abundance and in macroeconomic outcomes. Second, the fiscally autonomous environment implies that state governments benefit from their natural resource endowments to a considerable, and economically meaningful extent, so that they have impact at the local level.[20] Third, data availability enables us to test the hypothesis over a large period of time of over five decades. Last, such a setting enables us to examine the impact of national TFP shocks, across cross-sectional differences in endowments of natural resources that, on their own, are plausibly too small to impact national aggregate shocks. These features allow us to identify the causal link running from TFP shocks to output and inputs via the intensity of natural resources.

An examination of the heterogeneous contemporaneous effects of technology changes for different levels of resource abundance across states is based on two key measures: TFP shocks at the macroeconomic level and resource abundance at the state level. For the TFP shocks we follow BFK, and employ the purified utility-adjusted technology shocks of Fernald (2014), annualized via aggregations of the corresponding quarterly observations.[21] As outlined above, we assume that each state on its own is not sufficiently large to alter national technology patterns, including importantly via its natural resource wealth, so that we can consider TFP shocks to be exogenous for each state.[22] Table A1 of Appendix A notes that the mean TFP shock is close to 1, but the standard deviation is around 1.3. Hence, the data series contains periods of technology advancement as well as regress. Figure 3 plots this measure over our sample period.

As for resource abundance, we use the measure of state resource endowments constructed by James (2015). This measure is based on the cross-sectional difference in geologically-based recoverable stocks of crude oil and natural gas. Originally, it was interacted with the international oil price. However, we consider the cross-sectional dimension only in order to minimize endogeneity concerns, and in an attempt to focus on the temporal dimension

[19] However, we also undertake a county-level analysis, presented as robustness due to limitations of some of the main measures employed. We describe the related data separately in the corresponding sub-section.

[20] These benefits accrue regardless of whether the natural resources are located on state-owned or federal-owned lands. In the former case, state governments collect severance taxes and royalties. In the latter case, they benefit from shared federal revenues that amount to approximately 50% (but 90% in the case of Alaska) of the royalties paid to the federal government for oil production undertaken on these lands.

[21] We employ this measure within our baseline analysis, but also examine a number of additional TFP measures to check for robustness in a later sub-section.

[22] We do, however, examine later in the analysis sub-samples in which the largest states are excluded.

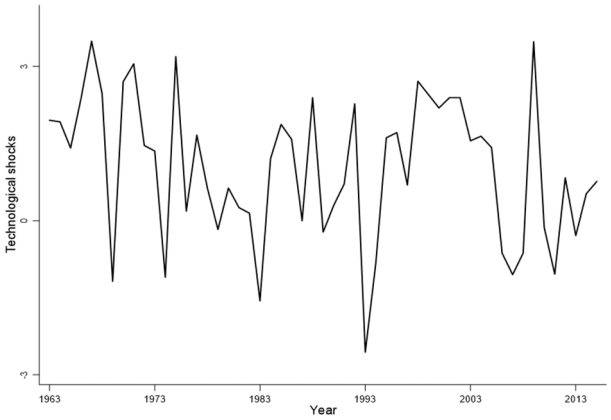

Fig. 3 Annualized technological changes in the U.S., 1963–2015. Source: Fernald (2014)

on the national TFP shocks, and their manifestation via resource intensity.[23] This data is derived from the U.S. Geological Survey at the province level, which James (2015) aggregates to the state level.[24] This provides the average endowment of natural resources per state, which we then normalize by state personal income, averaged over 1958–2008.

This measure is appealing for several reasons. First, due to its geologically-based perspective, it provides plausibly exogenous variation in resource abundance levels across states. Second, it provides ample variation across states. Specifically, given the usage of recoverable stocks of reserves, only seven states have near-zero natural resource endowments.[25] The average natural resource endowment ranges from none (e.g., Delaware) to slightly above 3% of state income (Wyoming), with a mean of 0.2% and a standard deviation of 0.6%.[26] Figure 4 plots the average level of this measure across the 48 continental U.S. states. Importantly, despite being geologically-based, this measure is highly correlated with changes in oil production and revenues, as illustrated by James (2015). Last, it bears little correlation (approximately -0.01) with average state income, i.e., at the cross-section level resource richness is not systematically associated with output. Indeed, some of the resource-rich states have on average higher output per capita (e.g., North Dakota), while others less so (e.g., Louisiana).

4.2 Identification and Estimation Methodology

Our identification strategy rests on two identifying assumptions. First, national TFP shocks are exogenous to any specific state, so no state on its own is sufficiently large to affect such shocks significantly. Second, the cross-sectional geologically-based recoverable stocks of oil and gas represent pre-determined, geographically entrenched endowments. Under these

[23] We do show in a later sub-section that the main patterns observed are robust to further interactions with the international oil price.

[24] This measure excludes Alaska (AK) and Hawaii (HI), thus restricting our sample to the 48 continental states.

[25] These states are Connecticut, Delaware, Massachusetts, Maine, New Hampshire, New Jersey, and Rhode Island. Several more states have positive, but scarce levels of natural resource endowments (see Figure 4).

[26] Notably, the vast cross-state variation enables testing the impact of natural resource abundance, regardless of their absolute levels. This approach follows the strand of literature that examines the effects of resource intensity via the case of U.S. states (e.g., Raveh 2013; James 2015).

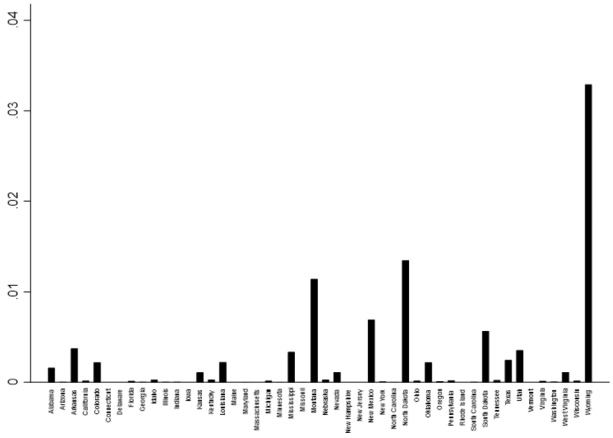

Fig. 4 Average resource endowment across the 48 continental U.S. states. Source: James (2015)

circumstances, both measures are not only plausibly exogenous to each other, but also when they are interacted they produce variations across space and time that are plausibly exogenous to state indicators. Hence, we employ a standard panel fixed-effects framework to estimate

$$\begin{aligned}\Delta(outcome)_{i,t} = \alpha + \beta(outcome)_{i,t-1} + \gamma(resource)_i \\ + \delta(tfp)_t + \theta(resource * tfp)_{i,t} + \eta_i + \nu_t + \epsilon_{i,t},\end{aligned} \tag{4}$$

where i indicates the state and t the year. Here $outcome$ denotes one of the following variables: real per capita output, real per capita capital stock, or the unemployment rate, each in natural logarithm form.[27] These outcome variables represent the key macroeconomic indicators examined by BFK, namely income and inputs.[28] In addition, η_i and ν_t denote the state and year fixed effects, respectively. These control for state and time-invariant unobservable effects. Last, tfp and $resource$ are the TFP shocks and resource abundance measures discussed in Sect. 3. Both are outlined in the model for completeness, yet they are absorbed by ν_t and η_i, given that they change only across time or states, respectively. The dependent variable is in changes, where Δ denotes the change between periods $t-1$ and t, with the level in $t-1$ added as a regressor to control for potential convergence. This is consistent with the dynamic perspective of the proposed mechanism.[29]

All variables are derived from the U.S. Census Bureau and the Bureau of Economic Analysis with the exception of state capital stocks. These stocks are derived from Garofalo and Yamarik (2002), and the data series for tfp and $resource$(outlined above). Standard errors are clustered by state in all cases. Appendix A outlines the variables and their source, where Table A1 presents descriptive statistics. Our focus throughout the analysis is on the sign, magnitude, and preciseness of the parameter θ, which provides an estimate for the impact of technology shocks across different levels of resource abundance levels. In addi-

[27] This form enables us to minimize the potential biasing impact of outliers. Examining the non-transformed form yields qualitatively similar results.

[28] BFK considered hours worked; we, however, examine in lieu the unemployment rate as it enables extending the sample period covered significantly, by more than three decades.

[29] Examining the dependent variable in changes, we in effect consider investment rates in the case of the capital stock as $outcome$.

tion, we also examine the characteristics of the effect of TFP shocks on outcomes, measured by the parameter δ, in various versions of our model that exclude ν_t and examine the impact of $(tfp)_t$ directly within restricted, separate, samples of resource-rich and resource-poor states.

4.3 Preliminary: Revisiting BFK with Natural Resources

The contemporaneously contractionary nature of technology improvements has been illustrated previously in the seminal work of BFK. Examining the impact of national TFP shocks on various U.S. macroeconomic indicators, BFK found that on impact technology improvements contract input use, most notably labor. Re-examining the contemporaneous effects of TFP shocks we, as a first step, incorporate our proposed dimension into BFK's framework, focusing on the impact on labor. We thus estimate a model reminiscent of the one estimated by BFK,

$$\Delta(unemp)_{i,t} = \alpha + \sum_{j=0}^{j=4} \beta(tfp)_{t-j} + \gamma(Year)_t + \eta_i + \epsilon_{i,t}, \tag{5}$$

where tfp, and η are described above, $unemp$ denotes the unemployment rate, and $Year$ is a time trend, in lieu of the time fixed effects, which are excluded in this framework due to their absorption of the state-invariant TFP shocks. Similar to BFK, contemporaneous TFP shocks are added together with four lags of TFP shocks.[30] Our focus in this specification is on β_0, which gives the contemporaneous effect of the TFP shock, $(tfp)_t$.

Our analysis differs from BFK in three respects. First, BFK considered the sample period of 1949–1996, which is not feasible for us due to lack of data at the state level. But, BFK also showed that their main results hold under the shorter sample period of 1980–1996. To undertake an effective comparison, we focus on this shorter sample period. Second, BFK examined national outcomes, constructing them via industry-level data. We, however, undertake an analysis across states, each with its own industrial composition.[31] Third, BFK examined the impact of TFP shocks vis-à-vis the aggregate sample. Our hypothesis, however, focuses on the abundance of natural resources, hence we split the sample into resource-rich and resource-poor states so that we can examine the impact of TFP shocks on each, separately. The threshold we adopt for this split is the 25th percentile of the baseline cross-sectional resource endowment measure outlined previously, in which states below it are categorized as resource poor. Such a division enables us to focus on the behavior of the cases of interest, namely those that represent little to no natural resource endowments.[32]

The results are outlined in Table 1. Column (1) examines the complete sample, where the resource-rich and -poor states are not split up. The results follow the patterns observed in BFK. Specifically, contemporaneous technology improvements boost changes in the unem-

[30] We follow BFK's specification to enable close comparison. We note that the estimation results are robust to using any number of lags up to the four used.

[31] Later, we also account for industrial composition, showing that the key dimension in this composition is the extractive industry.

[32] These represent the cases of interest, as according to our analysis, they raise the potential for contemporaneously non-contractionary patterns.

Table 1 TFP shocks and the unemployment rate for resource-rich and resource-poor states, 1980–1996 (revisiting BFK)

	(1)	(2)	(3)	(4)	(5)
	complete sample	with resources	without resources	with resources	without resources
Dependent variable:	change in unemployment rate	change in unemployment rate	change in unemployment rate	unemployment rate	unemployment rate
TFP	**0.12****	**0.22*****	**-0.15*****	**0.34*****	**-0.19***
	(0.05)	**(0.06)**	**(0.05)**	**(0.05)**	**(0.09)**
TFP (t-1)	-0.49***	-0.46***	-0.57***	0.21***	-0.32***
	(0.04)	(0.06)	(0.04)	(0.05)	(0.09)
TFP (t-2)	-0.45***	-0.5***	-0.31***	-0.11**	-0.58***
	(0.03)	(0.04)	(0.03)	(0.05)	(0.08)
TFP (t-3)	-0.07**	-0.15***	0.15**	-0.29***	-0.43***
	(0.03)	(0.03)	(0.07)	(0.04)	(0.04)
TFP (t-4)	0.21***	0.17***	0.33***	-0.21***	-0.4***
	(0.03	(0.03)	(0.07)	(0.04)	(0.04)
R-squared	0.24	0.29	0.32	0.77	0.84
Observations	912	669	243	669	243

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is the natural logarithm of the unemployment rate (Columns 4-5), or changes in thereof (Columns 1-3). All regressions include an intercept, a time trend, and state fixed effects. The sample includes the 48 continental U.S. states and covers the period of 1980-1996. 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). 'With/without resources' divides the sample based on the 25th percentile of the per capita resource endowment measure (described in the text). For further information on variables see data Appendix.

ployment rate and thus decreases the change in labor, yet in the periods thereafter they expand it. Columns (2) and (3) report results when the sample is split into resource-rich and -poor states, respectively. The outcome for the contemporaneous impact shows that for the resource-rich sub-sample, technological improvements are contractionary, but for the resource-poor sample such improvements are expansionary. Hence, the natural resources dimension is potentially an important aspect in the interpretation of the key results of BFK.[33] In addition, the results in columns (2) and (3) further indicate that in the longer term, labor expands more strongly in the resource-rich sample, despite the initial drop.

However, Christiano et al. (2004) addressed concerns related to potential endogeneity of the BFK measure. In addition, they considered the level of (rather than changes in) the labor input measure, and found a contemporaneous positive impact of TFP improvements on labor input. Christiano et al. (2004) thus found that TFP shocks are contemporaneously expansionary.

In our state-level setting concerns related to the endogeneity of TFP shocks are mitigated given their national perspective. Hence, to illustrate that correcting for the effect of the natural resources dimension may represent a reconciliation between the findings of BFK and Christiano et al. (2004), we re-estimate our results for columns (2) and (3) when the dependent variable (i.e., the unemployment rate) is in levels rather than in changes. The results appear in columns (4)-(5). They are similar to those reported in columns (2)-(3): technology improvements are contractionary in resource-rich and expansionary in resource-poor states.

[33] The potential relevance of the natural resources dimension to the interpretation of BFK's findings has been implied by Bils (1998), who pointed at the potential over-estimating effect of the oil price instrument used in BFK's analysis. Nonetheless, as will be noted in our main analysis, we illustrate that the observed patterns extend to various measures, and are not specific to those used in BFK.

4.4 Core Results on Impact of TFP Shocks

We now turn to our core results on the heterogeneous impacts of TFP shocks and how these depend on resource wealth in a more complete and rigorous setting, and with an expanded sample. We estimate various versions of Eq. (4), for each of the three $outcome$ variables. These core results are presented in Table 2.

4.4.1 Effects on Output

Starting with output, measured by the Gross State Product (GSP), Column (1) represents our core specification and provides support for our main hypotheses. The estimated value of θ is negative and statistically significant, which indicates that contemporaneous technology improvements indeed induce a stronger negative impact in resource-rich states than in resource-poor states, substantiating the main analytical prediction. In terms of magnitude, under the mean endowment of natural resources, a one standard deviation increase in TFP contracts average output of resource-rich states by 0.1% relative to output of resource-poor states.[34] Under an alternative interpretation, given an average resources level, a technological improvement that amounts to the annual mean level (i.e., the average improvement undertaken each year over time) contracts the output level of resource rich states relative to their resource poor counterparts by 0.007%, being the equivalent of about $800 million difference between the two state groups.[35]

Notably, the magnitude of this estimate of θ suggests that the outcome is not only in relative terms (noting that some states have no resource endowments). Furthermore, it points at a divergent outcome (cf. Table 1). This is also illustrated by columns (2) and (3) of Table 2. In the latter, we estimate a version of Eq. (4) which excludes ν and θ and examines the direct impact of TFP shocks via δ under the two separate sub-samples. This attempts to examine whether the main outcome is the result of a relative effect (resource-rich relative to resource-poor states), or a direct one driven by resource intensity. We focus on examining the sign, interpreting the magnitude with caution due to the exclusion of the time fixed effects. Fol-

Table 2 Resource endowments and effect of technology improvements, 1963–2015

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GSP			Unemployment			Investment		
	TFP	with resources	without resources	TFP	with resources	without resources	TFP	with resources	without resources
TFP		-0.003***	-0.0005		0.01***	-0.004		-0.005***	-0.004***
		(0.001)	(0.001)		(0.003)	(0.006)		(0.001)	(0.001)
Resources X TFP	-0.48***			0.87**			-0.02		
	(0.08)			(0.39)			(0.06)		
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	No	No	Yes	No	No	Yes	No	No
R-squared	0.88	0.86	0.86	0.61	0.64	0.67	0.91	0.87	0.88
Observations	2480	1933	547	1912	1485	427	2480	1933	547

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is real per capita Gross State Product (Columns 1-3), the unemployment rate (Columns 4-6), and real per capita investment (Columns 7-9), each in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states and covers the period of 1963-2015 (1975-2015 in Columns 4-6). 'Resources' denotes the resource endowment measure described in the text. 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). 'With/without resources' divides the sample based on the 25th percentile of the per capita resource endowment measure (described in the text). For further information on variables see data Appendix.

[34] This is computed by multiplying the estimated value of θ by the mean resource endowment and the standard deviation of TFP, and examining the change that this induces in the mean output measure.

[35] Similar to the previous case, this is computed by multiplying the estimated value of θ by the mean resource endowment and the annual mean TFP level, and dividing by the mean output level. The monetary value is computed by considering the 0.007% amount of the average annual state output level.

lowing the previously outlined division, the sub-sample in column (2) includes states with a per-capita resource endowment above the 25th percentile while the sub-sample in column (3) includes the remaining states with little or no resource endowments.

We observe that contemporaneous TFP shocks have a negative and statistically significant impact on output if there are some natural resource endowments. Conversely, if resource endowments are scarce, the impact becomes statistically imprecise with a magnitude close to zero. These outcomes clarify the source of the observed relative difference. They point at a distinct diverging outcome, similar to the patterns noted previously in our BFK exercise reported in Table 1, and consistent with our analytical predictions.

4.4.2 Effects on Unemployment and Capital

Columns (4)-(6) and (7)-(9), present an analysis similar to that presented in columns (1)-(3) yet with the labor or capital input proxies (namely, the unemployment rate or investment, respectively) as $outcome$. Columns (4) and (7) examine the complete sample whereas columns (5)-(6) and (8)-(9) consider the split samples based on the same division used before.

For the case of labor, the estimated value of θ in column (4) points at a similar outcome as observed under output. Specifically, technology improvements contract the labor market more strongly if natural resource endowments are high. Similar patterns are also observed in columns (5)-(6), since the estimated values of δ indicate that the contractionary effect occurs only in the group of states that are endowed with significant natural resources.

The outcomes in columns (8)-(9) show that investment contracts similarly in both types of environments following a positive TFP shock. This is further confirmed by the outcome in column (7), which points at no statistically distinguishable impact of TFP shocks on investment across resource intensity levels. These patterns, in conjunction with those observed for the effects on labor, are consistent with our analytical predictions given the previously established systematic differences in elasticities of substitution between labor and capital for resource-rich and -poor states, to the extent that the TFP shocks are capital-augmenting. Next, we examine this analytical prediction.

4.5 Effects of Capital- and Labor-Augmenting TFP Shocks

Our analytical predictions indicate that capital-augmenting shocks trigger contemporaneous substitution between capital and labor with a magnitude that depends on the size of the elasticities of substitution between labor and capital, hence contracting the labor input in resource-rich states. Here we examine the differential impact of capital- and labor-augmenting TFP shocks. We do so by employing the z_{nt} and z_{kt} parameters computed and outlined previously in Sect. 3.5, corresponding to labor- and capital-augmenting shocks, respectively. Given the scope of the underlying U.S. industry data, the computed parameters are available annually for the period 1998–2015.

We estimate our baseline specification, as per column (1) of Table 2, where now the z_{nt} and z_{kt} measures enter in lieu of tfp, separately. The results are presented in in Table 3. Columns (1)-(3) and (4)-(6) examine the case of z_{kt} and z_{nt}, respectively. In each case, the first, second, and third column examine the $outcome$ related to the output, labor, and capital measure, respectively.

Table 3 Effects of capital- and labor-augmenting TFP shocks, 1998–2015

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Capital augmenting			Labor augmenting		
	GSP	Unemployment	Investment	GSP	Unemployment	Investment
Resources X Zk	-0.43***	0.91***	0.19			
	(0.06)	(0.19)	(0.21)			
Resources X Zn				-0.04	0.02	-0.04
				(0.03)	(0.01)	(0.03)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.85	0.61	0.82	0.84	0.12	0.82
Observations	857	857	857	857	857	857

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is real per capita Gross State Product (Columns 1 and 4), the number of unemployed individuals per capita (Columns 2 and 5), and real per capita investment (Columns 3 and 6), each in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states and covers the period of 1998-2015. 'Resources' denotes the resource endowment measure described in the text. 'Zk' ('Zn') denotes the capital (labor) augmented technology changes computed from the model vis-à-vis data from the EUKLEMS dataset (O'Mahony and Timmer (2009)). For further information on variables see data Appendix.

These results are consistent with our analytical predictions. The estimated values of θ indicate that the differential impact across resource intensity levels is observed only under capital-augmenting shocks, and most notably with respect to output and labor input. This is consistent with the view that capital-augmenting shocks induce substitution between capital and labor more strongly in states where this substitution is stronger, i.e., resource-rich states, as suggested by our model.

4.6 Robustness Tests

We now conduct various robustness tests to see whether our core findings survive if we allow for other sectors than natural resources, different aggregate shocks, or different TFP measures, and when the resource measure is interacted with the world oil price. We also examine the level of U.S. counties, and test for robustness using different sample restrictions, controls, and specifications.

Tables 4 and 5 present the robustness results when we allow for other sectors than natural resources, or different aggregate shocks, respectively. The other robustness results are presented in Table 6. All specifications follow the core specification, unless otherwise specified, and they cover different time periods (depending on data availability), as stated in the table.

4.6.1 Results with Other Sectors than Natural Resources

Our core analysis has focused on one dimension of the industrial composition of states, i.e., resource abundance. To further motivate this focus, we also examine the role of other major sectors. We thus consider the GSP share of four major aggregate sectors: manufacturing, services, agriculture, and wholesale trade.[36] To examine how they might affect the impact of

[36] Each, as estimated by Young (2013), with a significantly lower ESKL, compared to that estimated for the oil and gas sector (taking manufacturing as an average of its sub-sectors).

Table 4 Results with other sectors than natural resources, 1963–2015

Dependent variable: real per capita Gross State Product	(1)	(2)	(3)	(4)	(5)
	Manufacturing	Services	Agriculture	Wholesale	All
Resources X TFP	-0.39***	-0.41***	-0.44***	-0.42***	-0.29***
	(0.09)	(0.08)	(0.1)	(0.06)	(0.1)
Manufacturing X TFP	0.001				0.001
	(0.001)				(0.001)
Services X TFP		0.02*			0.06
		(0.01)			(0.06)
Agriculture X TFP			-0.0004		0.03*
			(0.001)		(0.02)
Wholesale X TFP				0.002	-0.01
				(0.005)	(0.01)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.88	0.88	0.88	0.88	0.88
Observations	2480	2480	2480	2480	2480

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is real per capita Gross State Product in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states and covers the period of 1963-2015. 'Resources' denotes the resource endowment measure described in the text. 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). 'Manufacturing'/'Services'/'Agriculture'/'Wholesale' refer to the GSP share of the manufacturing/services/agriculture/wholesale sectors, respectively. For further information on variables see data Appendix.

Table 5 Results with different aggregate shocks

Dependent variable: real per capita Gross State Product	(1)	(2)	(3)	(4)	(5)
	Monetary	Federal taxation	IST news	Business cycles	All
Resources X TFP	-0.54***	-0.24***	-0.55***	-0.48***	-0.61***
	(0.19)	(0.07)	(0.09)	(0.08)	(0.18)
Resources X Monetary	-0.71**				-0.7***
	(0.28)				(0.24)
Resources X Federal_tax		-0.28***			0.93***
		(0.06)			(0.14)
Resources X News			-0.37**		0.8***
			(0.14)		(0.12)
Resources X Cycles				0.35***	0.42***
				(0.08)	(0.08)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.85	0.86	0.87	0.88	0.85
Observations	1856	2096	2288	2480	1856

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is real per capita Gross State Product in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states and covers the overall period of 1963-2015 (changing by column, depending on data availability). 'Resources' denotes the resource endowment measure described in the text. 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). 'Monetary' is monetary policy shocks derived from Tenyero and Thwaites (2016). 'Federal_tax' is federal tax shocks derived from Romer and Romer (2010). 'Cycles' is a business cycle indicator derived from the U.S. Federal Reserve. 'News' is Investment Specific Technology (IST) news shocks derived from Ben-Zeev (2018). For further information on variables see data Appendix.

TFP shocks, we interact them each with tfp and add them separately, and then concurrently, to the core specification. We will focus on output.

The results are presented in Table 4. In columns (1)-(4) we add each of the additional interaction terms separately, in conjunction with our interaction term of interest, $resource * tfp$. The outcome in each case indicates that our core results are robust to these inclusions, i.e., the estimated value of θ maintains its sign and precision. The robustness of θ is further observed in the demanding specification undertaken in column (5), in which all interaction terms are added concurrently. Interestingly, while natural resource intensity retains its role in the effects of technology shocks, none of the other major sectors exhibit similar characteristics. In all cases the estimated coefficients on the additional interaction terms have close to zero magnitudes and no statistical significance,[37] thus reaffirming the role of natural resources in understanding the effects of TFP shocks on state-level outcomes.

[37] Services and agriculture yield marginally precise patterns, but appear in only one of the specifications. Hence, these effects are not robust.

Table 6 Further robustness tests

Dependent variable: real per capita Gross State/County Product	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	County analysis			TFP measures			Additional tests									
	TFP	Capital Augmenting	Labor Augmenting	Ford	BS	JPT	Pre-1997	Post-1996	Controls	Quarterly -based analysis	Two-way clustering	Resource-rich excluded	No-resources excluded	Largest states excluded	Price	State-level TFP
Resources X TFP	-0.13*** (0.03)						-0.15** (0.71)	-2.37*** (0.2)	-0.66*** (0.1)	-0.39*** (0.03)	-0.48*** (0.17)	-1.46*** (0.3)	-0.47*** (0.07)	-0.47*** (0.08)		
Resources X Zk		-0.33*** (0.06)														
Resources X Zh			0.03 (0.02)													
Resources X Ford				-2.89*** (0.39)												
Resources X BS					-0.76*** (0.14)											
Resources X JPT						-2.29*** (0.17)										
Price X TFP															-0.02*** (0.002)	
Resources X State_TFP																-1.36*** (0.5)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year fixed effects	No	No	No	No	No	No	No	No	No	Yes	No	No	No	No	No	No
R-squared	0.59	0.54	0.54	0.86	0.87	0.86	0.85	0.84	0.89	0.89	0.88	0.88	0.87	0.88	0.88	0.88
Observations	80594	31913	31913	2192	2096	2192	1576	904	1952	2064	2480	2328	2272	2330	2480	2480

Notes: Standard errors are robust, clustered by state (by county in Columns 1-3; by state and year in Column 11), and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1%level of significance. The dependent variable is real per capita Gross State (or county, in Columns 1-3) Product in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states (in Column 12 the sample excludes the three most resource-rich states: Montana, North Dakota, and Wyoming; in Column 13 the sample excludes states with zero resource endowments: Delaware, Maine, New Hampshire, and Rhode Island; in Column 14 the sample excludes the largest states: California, New York, and Texas) and covers the period: 1963-2015 in Columns 11-15, 1970-2015 in Columns 1-3, 1963-1996 in Column 7, 1997-2015 in Column 8, 1964-2009 in Columns 4 and 6, 1964-2007 in Column 5, 1975-2015 in Column 9, 2005-2015 in Column 10. The sample in all columns is annual-based, with the exception of Column 10 in which the sample is quarterly-based; similarly, the time fixed effects in all columns refer to year fixed effects, whereas in Column 10 they refer to quarter fixed effects. 'Resources' ('Price') denotes the resource endowment measure described in the text (interacted with the international price of oil). 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). 'State_TFP' is an interaction of 'TFP' with the 2002-2007 state estimates of changes in measured state TFP changes from Caliendo et al. (2018). 'Zk' ('Zh') denotes the capital (labor) augmented technology changes computed from the model vis-à-vis data from the EUKLEMS dataset (O'Mahony and Timmer (2009)). 'Ford' denotes the TFP series of Francis et al. (2014). 'BS' denotes the Barsky-Sims TFP News series (Barsky and Sims (2011)). 'JPT' denotes the TFP series of Justiniano, Primiceri, and Tambolotti (2011). 'Controls' include tax revenues per capita, population, government expenditure per capita, debt per capita, unemployment rate, party affiliation of governor, and inequality (Theil Index). For further information on variables see data Appendix.

4.6.2 Results with Different Aggregate Shocks

Our main hypothesis pertains to the impact of TFP shocks. For identification purposes, we consider aggregate, national TFP shocks, as they are exogenous to each individual state. Nonetheless, their temporal variation may correlate with other concurrent national shocks with heterogeneous impacts across the natural resource dimension, especially as TFP shocks capture noise in aggregate production by construction. To address this, we consider additional national shocks, focusing on the impact of their interaction with the *resource* measure, in conjunction with the effect of our main interaction term of interest.

We consider four additional shocks at the aggregate, national U.S. level: monetary policy shocks, federal tax shocks, news shocks, and business cycles. For monetary shocks, we consider the data series constructed by Tenreyro and Thwaites (2016); considering federal tax shocks, we employ the narrative-based federal tax changes from Romer and Romer (2010); news shocks are represented by the Investment Specific Technology (IST) news shocks of Ben-Zeev (2018); last, business cycles are examined via an indicator that captures whether the U.S. is in a recession, as defined by the U.S. Federal Reserve.[38] We interact each measure with *resource*, and add each separately to the baseline specification, as per as per Column (1) of Table 2.[39]

The results are presented in Table 5. Columns 1–4 report the outcomes under each aggregate shock, in the order that appears above, respectively. Thereafter, column 5 presents the results of a specification in which all shocks are concurrently included. The estimated coefficients indicate that, consistent with Perez-Sebastian et al. (2019) and Perez-Sebastian and Raveh (2019), resource-rich states have better absorption of contractionary federal tax changes, and interestingly also of national recessions. In addition, consistent with Raveh (2020), resource-rich stats are impacted more strongly by contractionary monetary

[38] Each is available for a different sample period, as outlined in the Data Appendix; hence, sample size differs across cases.

[39] Similar to TFP, each (non-interacted) aggregate shock is captured by the year fixed effects, and hence excluded.

shocks.[40] Importantly, however, θ maintains its sign, significance, and magnitude, in all cases, including in the one in which all interaction terms are considered concurrently, thus further motivating the focus on national technology changes in the analysis.

4.6.3 Results at the U.S. County Level

While the availability of some of our data is limited at the more granular county level, examining our hypotheses under the measures that are available at the county level enables us to exploit a significantly larger sample of more than 3,000 counties. To measure cross-sectional resource endowments at the county level, we employ the plausibly exogenous resource measure constructed by James and Smith (2017). This provides a geologically-based indicator for counties with reserves of shale gas. We examine the impact of tfp, zk, and zn on county per-capita output, by interacting each of these with the county resource measure. Results are presented in columns (1)-(3) of Table 6, respectively. They indicate that our core result is robust at the county level, as we observe differential effects on output in the case of tfp and zk, but none for zn.

4.6.4 Results for Three Different Alternative TFP Measures

Columns (4)-(6) of Table 6 present estimation results for three different types of TFP measures. Our core estimates were done with the BFK measure, primarily in an attempt to create a more direct comparison to the BFK results. The literature, however, offers various measures of technology shocks, each with their own merits and limitations. To examine the validity of our results, we consider three additional data sources of TFP shocks: the FORD series (Francis et al. 2014), the BS series (Barsky and Sims 2011), and the JPT series (Justiniano et al. 2011). Each of the TFP types is interacted with our $resource$ measure and we use these instead of our baseline measure tfp. For each of these three alternative TFP measures, the estimated value of θ maintains its sign and precision. Our core results are thus robust to using these different types of TFP shocks.

4.6.5 Results with Different Sample Restrictions, Controls, and Specifications

Columns (7)-(14) of Table 6 present the results of some additional robustness tests that include different sample restrictions, controls, and specifications. First, motivated by the BFK exercise, we re-estimate our core specification prior to 1997 and after 1996, separately. This serves to test the applicability of the BFK case under the complete specification (not directly examined in the previous related sub-section), and examine whether our core results depend on that period. The estimated values of θ in columns (7)-(8) indicate that our core results are apparent in both periods, and that it intensifies in magnitude in the post-1996 period. This is consistent with the notion that technology improvements become more capital-oriented over time.

Next, we add various additional basic controls that may affect the impact of technology shocks indirectly, consider a specification with state-by-year fixed effects, and test the baseline specification under a different clustering method. In column (9), we include as controls government tax revenues per capita, government expenditure per capita, government

[40] The impact of IST news shocks is not robust, as the effect is unstable across specifications.

debt per capita, state unemployment rate, party affiliation of state governor, state inequality, and state population size. These controls account for various potential confounding factors at the state level, including the size of states (population), efficiency and size of states' public sector (taxes, expenditures, debt), states' business cycles (unemployment), political incentives of states' governors (party affiliation), and states' income polarization (inequality). In column (10) we consider a quarterly-based sample, in which both $outcome$ and $resource * tfp$ are quarterly-based (i.e., in this specification t represents a quarter-by-year cell). Such a specification enables adding state-by-year fixed effects, which control for all state-by-year changes, including the state indicators employed in column (9), as well as additional unobserved ones. The sample period in this case is 2005–2015, υ_t represents quarter fixed effects, and state-by-year fixed effects are included in lieu of η_i.[41] In Column (11) we then re-estimate our core specification with a two-way clustering method, where standard errors are clustered by state and year. The outcomes in all cases indicate that our main result is robust to these sensitivity examinations.

In columns (12)-(14) we re-estimate our model with three restricted samples. In column (12) we exclude Montana, North Dakota, and Wyoming. Figure 4 indicates that these states are outliers in terms of their resource richness, hence this exclusion enables us to examine the extent to which our core results are affected by them. In column (13) we exclude states with zero resource endowments (e.g., Delaware, Maine, New Hampshire, and Rhode Island). This addresses the potential concern that our core results are driven by states with no resources. In Column (14) we exclude California, New York, and Texas from the sample to test the robustness of our results when the three largest states are excluded. This restriction addresses the concern that our results may be driven by the dominant states. The estimated values of θ in all these cases indicate that our core results are robust to these restrictions on the sample.

4.6.6 Results When Resource Measure is Interacted with the Oil Price

Next, we interact the cross-sectional measure of resource endowment (used in our baseline) with the oil price which is plausibly exogenous (James 2015). This measure then enters the estimated equation instead of our core resource measure. We examine the effects of TFP shocks across states, but also within them across time. Column (15) presents the results. The estimated value of θ maintains its sign and significance under this interacted measure. This indicates that the impact of technology shocks does not only depend on the existence of resource endowments, but also on their value.

4.6.7 Results Under State-Level TFP Shocks

As a final robustness test, we examine the assumption about the homogeneity of the technological shocks across U.S. states. The baseline empirical analysis adopts this assumption in an attempt to address potential endogeneity concerns, noting that aggregate technological changes are plausibly exogenous to intra-state indicators. Our analytical framework takes a similar perspective under the assumption that TFP shocks are correlated across states due to the intra-federal setting. To examine the robustness of the results to this homogene-

[41] The sample period in this case is limited by the availability of data on Gross State Product at the quarter-by-year level.

ity assumption, we employ data from Caliendo et al. (2018). The latter estimated changes in measured TFP across U.S. states during two timeframes, 2002–2007, and 2007–2012. First, we note that the correlation of estimates across these two periods is highly positive, motivating the assumption about cross-state similarities in TFP patterns. Second, we adopt their estimates for the first period, as it is closer to the mid-point of our sample period, and consider them as cross-sectional differences in the absorption rate of national TFP changes, hence providing a cross-sectional dimension to the baseline national TFP measure.[42] Interacting this cross-sectional TFP measure with the baseline national TFP changes yields a state-level measure, with variations across both dimensions, namely states and time. We then employ this measure in lieu of tfp in the baseline specification. The results in column (16), under this modified specification, indicate that the main results hold and increase in an order of magnitude, thus pointing at the robustness of the analysis to the homogeneity perspective.

4.7 Longer-Term Effects of TFP Shocks

Our focus has been on the contemporaneous effects of TFP shocks. However, our analysis in Section 3 also gives insights concerning the dynamic patterns over time. Specifically, we find that resource-rich states should expand more strongly beyond the contemporaneous effect. Hence, we estimate and present the dynamic heterogeneous effects of TFP shocks across states with different levels of natural resources over the course of five years.[43] We employ the method of local-projections of Jorda (2005).

The method of local projections gives us estimates of impulse response functions separate regressions for each lead over the forecast horizon. The effect of TFP shocks at $t+h$ with $h = 0, 1, \ldots, 4$ is estimated by regressing dependent variables at $t+h$ on shocks and covariates at time t. Responses thus do not rely on nonlinear transformations of reduced-form parameters as in VARs.[44] We define $\Delta_{t-1} x_{i,t+h} \equiv x_{i,t+h} - x_{i,t-1}$ and estimate the sequential equations

$$\begin{aligned}\Delta_{t-1}(outcome)_{i,t+h} = \alpha^h + \beta^h(outcome)_{i,t-1} + \gamma^h(resource)_i \\ + \delta^h(tfp)_t + \theta^h(resource * tfp)_{i,t} + \eta_i^h + \nu_t^h + \epsilon_{i,t+h}.\end{aligned} \tag{6}$$

The dependent variable is cumulative growth of the $outcome$ variable, $\Delta_{t-1}(outcome)_{i,t+h}$, for different values of h. Our main coefficients of interest are the ones on the $resource * tfp$ interaction variable, i.e., θ^h for the contemporaneous effect $h = 0$ and the different leads $h = 1, \ldots, 4$. These 5 parameters shape the impulse response function, and hence enable us to trace the time profile of the effect of TFP shocks.

Figure 5 plots the impulse response functions for each of the outcome variables, together with 95% confidence intervals. For output, the gradual increase in the estimated value of

[42] For instance, during the 2002–2007 period the change in measured in TFP in Oregon was twice the size of that in Oklahoma, and three times that in New Hampshire.

[43] The length of the examined horizon is based on a 1-year extension of the BFK framework in which the effects of TFP shocks are observed, and measurable over the medium-term horizon of approximately four years.

[44] In Appendix B we present VAR estimates, and illustrate that the observed patterns are robust to the estimation method.

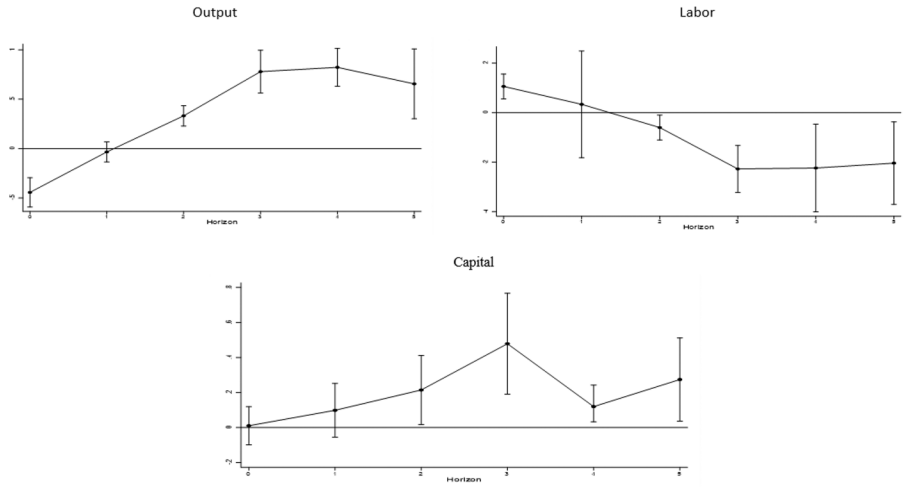

Fig. 5 Impulse response functions for the effect of TFP shocks. The figure presents the impact of technology shocks interacted with resource endowments on the natural logarithms of real per capita GSP, the unemployment rate, and real per-capita investment over a 5-year horizon, with 95% confidence intervals, following the method of local projections of Jorda (2005). The sample includes the 48 continental U.S. states and covers the period 1963–2015

θ^h, as the lead h increases, indicates that after the contemporaneous negative effect of TFP shocks, technology improvements become more expansionary in resource-rich states, most notably starting in the second year, relative to those in resource-poor states. The impulse response functions for labor and capital inputs paint a similar picture. This is evident from the gradually decreasing (increasing) patterns in the unemployment rate (investment), indicating again that positive TFP shocks are more expansionary in resource-rich environments, starting in the second year.

These patterns lend support to our analytical predictions, and importantly, they are also consistent with the outcomes noted in the initial BFK exercise in which the observed post-contemporaneous expansionary impacts (noted as well, under the general sample) were stronger for resource-rich states than for resource-poor states.

5 Conclusion

We have examined, both analytically and empirically, how technological shocks interact with natural resource abundance to affect growth in output and inputs. We offered a two-sector growth model with non-neutral technical progress and adjustment costs to show that cross-sector differences in the degree of substitution between capital and labor can induce corresponding differences in the contemporaneous and long-run reactions to technology improvements, most notably capital-augmenting ones. Using our model and U.S. industry data, we have computed elasticity parameters of different sectors, revealing that the ESKL is persistently higher in extractive industries. We have also computed time series for the capital- and labor-augmenting technology parameters and employed these in our empirical analysis.

We have tested our analytical predictions empirically using a panel of U.S. states over a period of five decades. We have examined in detail the impact of the interaction of national TFP shocks and states' resource abundance on growth in output and inputs of individual states. The use of national aggregate shocks and cross-sectional differences in geologically-based resource endowments has enabled us to examine the causal effects of technology changes on output and inputs, and how these effects are affected by the presence of natural resources.

Consistent with our predictions, the estimates point at divergent effects of technology improvements on growth in output and inputs across resource abundance levels, both in the short and in the longer term. In the short-run, we have observed that technology improvements, most notably capital-augmenting ones, are contractionary primarily in resource-rich states, and are non-contractionary or expansionary in resource-poor states. In the longer term, we have found that TFP shocks become more expansionary in resource-rich states relative to those in resource-poor states. We have shown that these results are robust to including various controls, treatment measures, aggregate shocks, sample restrictions, and specifications. In addition, we have showed that they also appear with the BFK methodology, data, and period, including when their setup is corrected for earlier concerns.

Our results help to understand how technological change may manifest the adverse effects of natural resource abundance on output. In turn, they also provide a potential reconciliation for the ongoing, inconclusive, debate on the short-run effects of technology improvements by recognizing the role of natural resources and the differences in the degree of substitution between labor and capital inputs. Our results also point to the need to account for the technological environment for purposes of resource management, as well as to take account of the substitutability between factor inputs when considering the impact of technology shocks.

These insights have the following policy implications. Policymakers in resource-abundant regions may consider implementing countercyclical labor market policies to mitigate short-term contractions caused by technology-driven labor displacement. This could include, for instance, targeted job training programs that equip workers with skills complementary to new capital-intensive technologies, thus reducing the likelihood of temporary unemployment spikes. Additionally, policies encouraging capital investment in downstream industries, such as resource-based manufacturing, may help smooth the transition and enhance the immediate productivity gains from technological improvements.

Furthermore, governments in resource-rich areas may consider adopting a phased approach to technological integration, ensuring that infrastructure and workforce development keep pace with capital-intensive innovations. This could involve, for example, tax incentives or subsidies for firms that invest in skill development alongside technology adoption. Policymakers may also consider establishing, or exploiting existing, sovereign wealth funds or stabilization funds to buffer against short-term economic contractions, using resource revenues strategically to support labor market flexibility. By implementing these measures, resource-rich regions can benefit from the long-term benefits of technological improvements while minimizing the risks of short-term disruptions.

Appendix

A. Proofs of the Propositions

Proof of Proposition 1

To derive the values of ω_{it} and Ω_{it}, we solve the firm's long-run problem. Denote by k^*_{it} and n^*_{it} the long-run levels of productive capital and labor for a given vintage. Hence, $n^*_{et} + n^*_{mt} = N$, and the values of k^*_{it} and n^*_{it} are given by the solution to

$$\max_{\{k^*_{it}, n^*_{it}\}} \left\{ p_i \left[\left(z_{kt} k^*_{it}\right)^{1-1/\varepsilon_i} + \left(z_{nt} n^*_{it}\right)^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1}} - R k^*_{it} - w_t n^*_{it} \right\}. \tag{7}$$

For simplicity, problem (7) assumes zero investment adjustment costs to obtain the long-run values of the inputs. The first-order optimality conditions for capital and labor are

$$p_i z_{kt} \left[z_{kt}^{1-1/\varepsilon_i} + \left(\frac{z_{nt} n^*_{it}}{k^*_{it}} \right)^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1} - 1} = R, \tag{8}$$

$$p_i z_{nt} \left[\left(\frac{z_{kt} k^*_{it}}{n^*_{it}} \right)^{1-1/\varepsilon_i} + z_{nt}^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1} - 1} = w_t. \tag{9}$$

The last two equalities can be combined to obtain the optimal effective capital per unit of effective labor. In particular, defining ω_{it} as this long-run ratio, we can write

$$\omega_{it} \equiv \frac{z_{kt} k^*_{it}}{z_{nt} n^*_{it}} = \left(\frac{z_{kt}}{z_{nt}} \frac{w_t}{R} \right)^{\varepsilon_i}. \tag{10}$$

Notice that the definition of ω_{it} guarantees that $n_{it} = n^*_{it}$ in the long-run.

Equations (9) and (10) for the non-extractive industry give the factor price frontier,

$$w_t = z_{nt} \left(1 - z_{kt}^{\varepsilon_m - 1} R^{1-\varepsilon_m}\right)^{1/(1-\varepsilon_m)}. \tag{11}$$

The wage rate, w_t, increases in the productivity of capital and of labor, z_{kt} and z_{nt}, and decreases in the interest, R, provided that $\varepsilon_m \neq 1$.

From (10) and (11), the optimal long-run effective capital per unit of effective labor is

$$\omega_{it} = \left[\left(\frac{z_{kt}}{R} \right)^{1-\varepsilon_m} - 1 \right]^{\varepsilon_i/(1-\varepsilon_m)}. \tag{12}$$

Hence, ω_{it} increases with capital productivity, z_{kt}. Labor producitivty, z_{nt}, on the other hand, does not affect relative effective use of inputs, ω_{it}, because the direct negative impact

of z_{nt} on ω_{it} and its indirect positive one on the wage cancel out exactly, which is a consequence of the production function having constant returns to scale.

Finally, by imposing the fixed input proportions dictated by Eq. (12) on production function (2), we can write

$$y_{it} = \left[1 + \omega_{it}^{(1-\varepsilon_i)/\varepsilon_i}\right]^{\varepsilon_i/(\varepsilon_i - 1)} z_{kt} k_{it}^*. \tag{13}$$

Comparing this last expression to Eq. (1), and noting that the Leontief specification implies that at the optimum $y_{it} = \Omega_{it} z_{kt} k_{it}^*$, we recover the value of Ω_{it} stated in the proposition.

Proof of Proposition 2

Notice that labor always moves towards the most productive sector and that, in the long run, the total level of employment equals the population size N. Consequently, if labor productivity increases in both sectors with both z_{kt} and z_{nt}, it is immediate that the economy's total level of output will increase as well in the long run. By imposing the fixed input proportions dictated by Eq. (12) on production function (2), we obtain labor productivity

$$\frac{y_{it}}{n_{it}^*} = z_{nt} \left(\omega_{it}^{1-1/\varepsilon_i} + 1\right)^{\varepsilon_i/(\varepsilon_i - 1)}. \tag{14}$$

To see how labor productivity varies with z_{nt} and z_{kt}, our next step is to take the derivative of the right-hand side of Eq. (14) with respect to these two productivity parameters. Define $\lambda_t = \left(\frac{z_{kt}}{R}\right)^{1-\varepsilon_m} - 1$. Note that $\lambda_t > 0$, since otherwise w_t cannot be positive according to Eq. (11). Then, we obtain

$$\frac{\partial y_{it}/n_{it}^*}{\partial z_{nt}} = \left(\frac{1}{z_{nt}}\right) \frac{y_{it}}{n_{it}^*}, \tag{15}$$

$$\frac{\partial y_{it}/n_{it}^*}{\partial z_{kt}} = \left[\frac{\varepsilon_i \left(\frac{z_{kt}}{R}\right)^{-\varepsilon_m}}{R\lambda_t}\right] \frac{y_{it}}{n_{it}^*}, \tag{16}$$

which are always positive. Consequently, we have established that the economy's long-run output level increases in both z_{nt} and z_{kt}.

Our next task is to analyze how the growth of labor productivity varies with $\varepsilon_i \neq \varepsilon_m$. Equation (15) implies that the growth rate of y_{it}/n_{it}^* induced by a change in z_{nt} only depends on the value of z_{nt}, and therefore, is independent of ε_i.

Conversely, the effect of ε_i on the growth of labor productivity caused by a change of z_{kt}, which is given by the terms within squared brackets in Eq. (16), is positive if and only if

$$1 + \lambda_t^{\frac{1-\varepsilon_i}{1-\varepsilon_m}} \left(1 + \frac{\varepsilon_i}{1-\varepsilon_m} \; ln\lambda_t\right) > 0. \tag{17}$$

Using L'Hopital rule, it is easy to show that, if $\varepsilon_i < 1$,

$$\lim_{\lambda_t \to 0} \frac{ln\lambda_t}{\lambda_t^{\frac{\varepsilon_i - 1}{1-\varepsilon_m}}} = \lim_{\lambda_t \to 0} \frac{1}{\frac{\varepsilon_i - 1}{1-\varepsilon_m} \lambda_t^{\frac{\varepsilon_i - 1}{1-\varepsilon_m}}} = 0,$$

and therefore, the last inequality holds under the restrictions on ε_e, ε_m, and z_{kt}/R stated in Proposition 2. Lastly, note that this result can be interpreted relative to the growth impact on the non-extractive activity, which is obtained when $\varepsilon_i = \varepsilon_m$ in Eq. (16).

Proof of Proposition 3

We start by recalling that in the short-run, capital and labor enter the production function in fixed proportions, and therefore, the level of employment can be below N. For example, the economy will have involuntary unemployment if k_i^*/n_i^* rises but $k_{et} + k_{mt} < k^* = k_e^* + k_m^*$, where $k_i^* = z_n \omega_i n_i^*/z_k$.

These fixed proportions are reflected in the values of ω_{it} and Ω_{it} defined in Proposition 1. Using these values, and imposing the optimality condition over capital and labor associated to the Leontief specification (i.e., $\omega_{it} z_{nt} n_{it} = z_{kt} k_{it}$), we can write the short-run production function, given by Eq. (1), in terms of the sectoral capital stock as

$$y_{it} = \Omega_{it} z_{kt} k_{it}. \tag{18}$$

Therefore, in the short run, the firm decides how much to invest in gross capital formation taking input prices, production function (18), and the adjustment costs as given. Specifically, the firm solves the problem subject to the motion of capital, which is determined by Eq. (3), and the constant input proportion condition given by Eq. (12). The return R is defined as in the long-run problem. Notice that, however, in the long-run problem, defined by expression (7), we have assumed no adjustment costs, so that one unit of investment capital provides one unit of productive capital. In the short run, this is not the case, and then, the sum operator next to R provides the borrowed investment capital that still earns interest payments from the firm.)[45]

$$\max_{x_{it}} \left\{ p_i \Omega_{it} z_{kt} k_{it} - R \sum_{j=1}^{t} (1-\delta)^{t-j} x_{ij} - w_t n_{it} \right\} \tag{19}$$

The first-order optimality condition to this problem (for an interior solution) is

$$x_{it} = \left(\Psi_{it} z_k \frac{\phi}{R} \right)^{\frac{1}{1-\phi}}, \tag{20}$$

[45] The terms affected by the sum operator in expression (37) provide the firm's pending debt (d_{it}), which is obtained by iterating the equation $d_{ij} = (1-\delta) d_{ij-1} + x_{ij}$ from $j = 1$ to t.

where $\Psi_{it} = p_i\Omega_i - \frac{w_t}{\omega_{it} z_{nt}}$. Hence, a lower value of ϕ reduces the optimal amount of investment, and convergence toward the new long-run stock of productive capital occurs at a lower speed.

Note that if ϕ is sufficiently low, the increase in k_{it} can be negligible. Under this scenario, Eq. (18) implies that y_{it} falls with z_{kt} if $\Omega_{it} z_{kt}$ falls. In the non-extractive sector, $\varepsilon_i = \varepsilon_m$, and then, Eq. (12) implies that $\Omega_{mt} z_{kt} = R^{\varepsilon_m} z_{kt}^{1-\varepsilon_m}$. Therefore, for values of ϕ sufficiently low, y_{mt} decreases in the short run with z_{kt} if and only if $\varepsilon_m > 1$. However, if $\varepsilon_m < 1$, y_{mt} always increases with z_{kt}.

In the extractive sector, it is easy to show that $\Omega_{et} z_{kt}$ decreases with z_{kt} if and only if

$$1 + \left[\left(\frac{z_{kt}}{R}\right)^{1-\varepsilon_m} - 1\right]^{(1-\varepsilon_e)/(1-\varepsilon_m)} < \varepsilon_e \left(\frac{z_{kt}}{R}\right)^{1-\varepsilon_m} \left[\left(\frac{z_{kt}}{R}\right)^{1-\varepsilon_m} - 1\right]^{(\varepsilon_m-\varepsilon_e)/(1-\varepsilon_m)}.$$

Note that if $\varepsilon_m = \varepsilon_e$, the last inequality becomes $1 < \varepsilon_e$. Hence, if $\varepsilon_e = \varepsilon_m > 1$, y_{et} decreases with z_{kt}. Additionally, when $\varepsilon_m < \varepsilon_e < 1$, the left-hand side of the inequality goes to 1, and its right-hand side goes to infinity as the value of $(z_{kt}/R)^{1-\varepsilon_m}$ goes to 1 from above. Therefore, another set of sufficient conditions for y_{et} to decrease with z_{kt} is when z_{kt}/R is sufficiently low and $\varepsilon_m < \varepsilon_e < 1$.

Regarding the effects of z_{nt}, they result from the independence of ω_i and Ω_i from z_{nt}.

B Model with Natural Resources

To introduce natural resources into the model, we assume that production in the non-extractive sector is still given by Eqs. (1) and (2) for $i = m$. However, short-run production in the extractive activity is now the result of combining labor, capital, and the stock of natural resources (denoted by n) according to

$$y_{et} = \Omega_{et} n^{\gamma} \left[\min\left\{z_{kt} k_{et}, \omega_{et} z_{nt} n_{et}\right\}\right]^{1-\gamma}, \tag{21}$$

where $\gamma \in (0, 1)$. Similarly, long-run production in e is given by

$$y_{et} = n^{\gamma} \left[\left(z_{kt} k_{et}\right)^{1-1/\varepsilon_e} + \left(z_{nt} n_{et}\right)^{1-1/\varepsilon_e}\right]^{\frac{\varepsilon_e}{\varepsilon_e - 1}(1-\gamma)}. \tag{22}$$

Now, y_{et} represents the flow of natural resources extracted from the ground at period t, while n denotes the stock of natural capital available for extraction. For simplicity, we assume that this stock is constant. Because the new input enters the production functions multiplicatively, it is easy to show that Propositions 1 to 3 hold with the new production functions for the extractive activity.

We finish this appendix with a final remark. In this extension of the model, we have assumed that the natural resource stock is constant. While this is clearly a restrictive assumption, we do not believe it significantly affects our main conclusions. The analytical model serves as a guide for interpreting the results obtained from the empirical analysis, which examines a sample of U.S. states from 1998 to 2015. The stock of natural resources and its extraction rates remained relatively stable in the U.S. from 1998 to about 2009, although they experienced a rapid increase thereafter (see, e.g., U.S. Energy Information Administra-

tion data at https://www.eia.gov). Crucially, this rapid increase should not amplify the negat ive short-run impact on output and labor. On the contrary, it would likely make these effects less pronounced, thereby reinforcing the robustness of our results.

C. Skilled Labor and Sector-Specific Productivity Shocks

The existence of skill-biased technical change has been widely documented in the literature (e.g., see Acemoglu 2002; Violante 2008). In this appendix, we illustrate how this type of technical change, along with the elasticity of substitution between physical capital and skilled labor may affect our main results.

In this version of the model, we consider three inputs used by sector i at time t: physical capital (k_{it}), skilled labor (s_{it}), and unskilled labor (n_{it}). The economy is endowed with a fixed amount N of unskilled workers who cannot cross borders. These inputs are combined according to the following short-run and long-run production functions, respectively,

$$y_{it} = \Omega_{it} \min \left\{ z_{kit} k_{it}, \theta_{it} z_{sit} s_{it}, \omega_{it} z_{nit} n_{it} \right\}, \tag{23}$$

$$y_{it} = \left\{ \left[\left(z_{kit} k_{it} \right)^{1-1/\mu_i} + \left(z_{sit} s_{it} \right)^{1-1/\mu_i} \right]^{\frac{\mu_i}{\mu_i - 1}(1-1/\varepsilon_i)} + \left(z_{nit} n_{it} \right)^{1-1/\varepsilon_i} \right\}^{\frac{\varepsilon_i}{\varepsilon_i - 1}}, \tag{24}$$

where z_{kit}, z_{sit}, and z_{nit} are the productivity levels of k_{it}, s_{it}, and n_{it}, respectively. Note that these productivity levels are now sector specific. The parameter μ_i represents the elasticity of substitution between physical capital and skilled labor, and ε_i is the elasticity of substitution between the capital-skill input bundle and unskilled labor.[46] Consistent with the evidence in favor of the capital-skill complementarity hypothesis (e.g., Krusell et al. 2000; Duffy et al. 2004; Raveh and Reshef 2016), we assume that physical capital is more complementary to skilled labor than to unskilled labor, and then $\varepsilon_i > \mu_i$.

In this version of the model, θ_{it} is the fixed ratio of $z_{kit} k_{it}$ to $z_{sit} s_{it}$, and ω_{it} is the fixed ratio of $z_{kit} k_{it}$ to $z_{nit} n_{it}$ used in production in the short run. For simplicity, we assume that both physical capital and skilled labor are mobile across states and countries. Therefore, their prices (R and w_{st}, respectively) are determined on world markets.

Similar to the benchmark model, the parameters Ω_{it}, θ_{it}, and ω_{it} must be consistent with the solution to the long-run problem. Denoting the long-run values of the variables with an asterisk, we can write this problem as

$$\max_{\{k^*_{it}, s^*_{it}, n^*_{it}\}} p_i \left\{ \left[\left(z_{kit} k_{it} \right)^{1-1/\mu_i} + \left(z_{sit} s_{it} \right)^{1-1/\mu_i} \right]^{\frac{\mu_i}{\mu_i - 1}(1-1/\varepsilon_i)} + \left(z_{nit} n_{it} \right)^{1-1/\varepsilon_i} \right\}^{\frac{\varepsilon_i}{\varepsilon_i - 1}} - R k^*_{it} - w_{st} s^*_{it} - w_{nt} n^*_{it}. \tag{25}$$

where w_{nt} is the wage rate of unskilled labor.

The first-order optimality conditions for this problem imply that

[46] This specification of the production function, where k_{it} and s_{it} are combined in a nested CES structure, and the resulting composite is then combined with n_{it} at a second nested level, has worked well in empirical investigations of the capital-skill complementarity hypothesis. See, e.g., Duffy et al. (2004)

$$p_i y_{it}^{1/\varepsilon_i} \left[(z_{kit} k_{it})^{1-1/\mu_i} + (z_{sit} s_{it})^{1-1/\mu_i} \right]^{\frac{\mu_i}{\mu_i - 1}(1-1/\varepsilon_i)-1} (z_{kit} k_{it})^{-1/\mu_i} z_{kit} = R, \quad (26)$$

$$p_i y_{it}^{1/\varepsilon_i} \left[(z_{kit} k_{it})^{1-1/\mu_i} + (z_{sit} s_{it})^{1-1/\mu_i} \right]^{\frac{\mu_i}{\mu_i - 1}(1-1/\varepsilon_i)-1} (z_{sit} s_{it})^{-1/\mu_i} z_{sit} = w_{st}, \quad (27)$$

$$p_i y_{it}^{1/\varepsilon_i} (z_{nit} n_{it})^{-1/\mu_i} z_{nit} = w_{nt}, \quad (28)$$

where y_{it} is given by Eq. (24).

Combining the optimality conditions (26) and (27) gives the optimal ratio of physical capital to skilled labor, so that

$$\theta_{it} \equiv \frac{z_{kit} k_{it}^*}{z_{sit} s_{it}^*} = \left(\frac{z_{kit}}{z_{sit}} \frac{w_{st}}{R} \right)^{\mu_i} \quad (29)$$

Equation (29) implies that θ_{it} increases in z_{kit}, decreases in z_{sit}, and is independent of z_{nit}.

In the same way, the optimality conditions (26) and (28) deliver the optimal ratio of physical capital to unskilled labor, which gives

$$\omega_{it} \equiv \frac{z_{kit} k_{it}^*}{z_{nit} n_{it}^*} = \left(\frac{z_{kit}}{z_{nit}} \frac{w_{nt}}{R} \right)^{\varepsilon_i} \left[1 + \left(\frac{z_{kit}}{z_{sit}} \frac{w_{st}}{R} \right)^{1-\mu_i} \right]^{\frac{\varepsilon_i - \mu_i}{\mu_i - 1}}. \quad (30)$$

It is easy to deduce from equation (30) that ω_{it} increases in z_{sit} and decreases in z_{nit}. In contrast, since z_{kit} appears twice in Eq. (30), we obtain the first derivative to know how ω_{it} is affected by changes in z_{kit}, namely

$$\frac{\partial \omega_{it}}{\partial z_{kit}} = \frac{\left(\frac{z_{kit}}{z_{nit}} \frac{w_{nt}}{R} \right)^{\varepsilon_i}}{z_{kit}} \left[1 + \left(\frac{z_{kit}}{z_{sit}} \frac{w_{st}}{R} \right)^{1-\mu_i} \right]^{\frac{\varepsilon_i - \mu_i}{\mu_i - 1} - 1} \left[\varepsilon_i + \mu_i \left(\frac{z_{kit}}{z_{sit}} \frac{w_{st}}{R} \right)^{1-\mu_i} \right]. \quad (31)$$

This last expression is always positive.

To summarize, given that $\varepsilon_i > \mu_i$, both equations (29) and (30) indicate that the optimal amount of an input relative to another input, both measured in efficiency units, varies directly with relative input productivity levels and inversely with relative input prices.

The prices of physical capital and skilled labor are given exogenously. However, the wage rate of skilled labor is endogenous. From equations (28) to (30), applied to the non-extractive sector (m), we can derive an expression for the wage of unskilled labor expressed as a function of exogenous variables and parameters,

$$w_{nt} = z_{nmt}\left[1-\left(\left\{\left(\frac{z_{kmt}}{R}\right)^{\varepsilon_m}\left[1+\left(\frac{z_{kmt}}{z_{smt}}\frac{w_{st}}{R}\right)^{1-\mu_m}\right]^{\frac{\varepsilon_m-\mu_m}{\mu_m-1}}\right\}^{1-1/\mu_m}\right.\right.$$
$$\left.\left.+\left\{\left(\frac{z_{smt}}{w_{st}}\right)^{\varepsilon_m}\left[\left(\frac{z_{smt}}{z_{kmt}}\frac{R}{w_{st}}\right)^{1-\mu_m}+1\right]^{\frac{\varepsilon_m-\mu_m}{\mu_m-1}}\right\}^{1-1/\mu_m}\right)^{\frac{\mu_m}{\mu_m-1}\frac{\varepsilon_m-1}{\varepsilon_m}}\right]^{\frac{1}{1-\varepsilon_m}}. \tag{32}$$

Therefore, the unskilled-labor wage rate depends only on variables and parameters related to the non-extracted sector. It can be easily shown that w_{nt} increases in z_{nmt}, z_{kmt}, and z_{smt}. Recall that, due to capital-skill complementarity, the optimal efficiency units of physical capital and skilled labor relative to those of unskilled labor increase in z_{kmt} and z_{smt}. This, along with the fact that there is always some degree of complementarity between the three inputs, implies that an increase in the productivity of any input raises the wage rate.

Substituting the fixed input proportions implied by Eqs. (29) and (30) into the long-run production function, given by equation (24), we obtain

$$y_{it} = \left\{\left[\omega_{it}^{\frac{\mu_i-1}{\mu_i}}+\left(\frac{\omega_{it}}{\theta_{it}}\right)^{\frac{\mu_i-1}{\mu_i}}\right]^{\frac{\mu_i}{\mu_i-1}\left(\frac{\varepsilon_i-1}{\varepsilon_i}\right)}+1\right\}^{\frac{\varepsilon_i}{\varepsilon_i-1}} z_{nit}n^*_{it}, \tag{33}$$

or, alternatively,

$$y_{it} = \left[\left(1+\theta_{it}^{\frac{1-\mu_i}{\mu_i}}\right)^{\frac{\mu_i}{\mu_i-1}\left(1-\frac{1}{\varepsilon_i}\right)}+\omega_{it}^{\frac{1-\varepsilon_i}{\varepsilon_i}}\right]^{\frac{\varepsilon_i}{\varepsilon_i-1}} z_{kit}k^*_{it}. \tag{34}$$

Moreover, comparing this last expression to the short-run production function, given now by Eq. (23), we deduce that

$$\Omega_{it} = \left[\left(1+\theta_{it}^{\frac{1-\mu_i}{\mu_i}}\right)^{\frac{\mu_i}{\mu_i-1}\left(1-\frac{1}{\varepsilon_i}\right)}+\omega_{it}^{\frac{1-\varepsilon_i}{\varepsilon_i}}\right]^{\frac{\varepsilon_i}{\varepsilon_i-1}}. \tag{35}$$

Equation (35) indicates that Ω_{it} decreases in both θ_{it} and ω_{it}. Therefore, Eqs. (29) and (30) imply that Ω_{it} decreases in z_{kit}, as in the benchmark case. However, in the new version of the model, both z_{nit} and z_{sit} also affect it—the former with a positive impact, while the latter has an ambiguous impact.

In what follows, we assume that $\frac{z_{kit}}{z_{nit}}\frac{w_{nt}}{R} > 1$ and $\frac{z_{kit}}{z_{sit}}\frac{w_{st}}{R} > 1$, since R is constant, but wages tend to increase with the economy. We first analyze the effects of productivity shocks on long-run output. In the long run, all the economy's available labor is used in production. Therefore, similar to what happens in the benchmark model, because labor is directed to the most productive activity, gains in any input productivity must result in gains in output. However, unlike in the benchmark model, since productivity shocks are now sector-specific,

long-run output will tend to increase more significantly in the sector where productivity parameters experience a larger rise.

Our next task is to determine how these long-run output gains induced by productivity shocks vary with the elasticities of substitution between inputs (ε_i and μ_i). The effects on long-run output can be inferred from Eq. (33), which is the relevant one because labor goes back to full employment in the long run, that is, $n^*_{et} + n^*_{mt} = N$. Therefore, we can assume that n^*_{it} does not vary significantly. We focus on the elasticities of the extractive activity, as we are interested in knowing, for example, how the different effects change when ε_e increases away from ε_m. From Eqs. (29) and (30), we see that ε_e does not affect θ_{et} but amplifies the positive effect of z_{ket} on ω_{et}. While this suggests a stronger positive effect, the presence of ε_i within the CES structure of the production function introduces an additional channel—hereafter referred to as the CES channel—through which changes in the elasticity of input substitution influence the overall outcome, leading to ambiguity.

This ambiguity implies that, as observed in the benchmark model, the effect operating through input proportion responses may dominate for some subsets of the input elasticity parameters. Moreover, in most cases, when analyzing the impact of ε_e and μ_e, the CES channel will deliver the same outcome in our analysis. Therefore, our discussion will henceforth focus primarily on the impact on input proportions, while keeping in mind that the results hold for specific values of the elasticity parameters.

Hence, the results so far are similar to those of the benchmark model. An increase in the elasticity of substitution between the capital-skill bundle and unskilled labor in the extractive industry has a clear effect on the input proportion responses, contributing to a stronger positive impact of long-run output to changes in z_{ket}. However, this result may hold only for certain values of ε_e.

In contrast, an increase in μ_e makes $\partial\theta_e/\partial z_{ket}$ more positive and $\partial\omega_{et}/\partial z_{ket}$ less positive. Equation (33) then suggests a weaker positive effect of capital-augmenting productivity on long-run output when the elasticity of substitution between capital and skilled labor increases in the extractive sector.

It is also easy to show that changes in the input elasticity parameters affect the long-run output response to skill-biased productivity shocks (z_{set}) in qualitatively the same way as they do for an increase in z_{ket}.,[47] Regarding the response to z_{net}, as ε_e rises, ω_{et} falls more, while θ_{et} does not vary. As a result, the impact of z_{net} weakens as ε_e increases, since capital rises less due to its greater substitutability with unskilled labor. Conversely, the impact of z_{net} on long-run output channeled through input proportions strengthens as μ_{et} rises.

We can thus draw the following conclusions. First, if the extractive industry exhibits a higher elasticity of substitution between capital and unskilled labor (i.e., $\varepsilon_e > \varepsilon_m$), there may exist values of ε_e and ε_m for which long-run output in the extractive sector rises more than in the non-extractive industry as a response to the same capital- or skill-biased productivity shock. Second, if the extractive industry has a higher elasticity of substitution between capital and skilled labor (i.e., if $\mu_e > \mu_m$), the opposite effect may occur—namely, long-run output may increase less in the extractive sector than in the non-extractive industry for

[47] This can be easily deduce by comparing Eq. (30), which gives

$$\frac{\omega_{it}}{\theta_{it}} = \left(\frac{z_{sit}}{z_{nit}}\frac{w_{nt}}{w_{st}}\right)^{\varepsilon_i}\left[1+\left(\frac{z_{sit}}{z_{kit}}\frac{R}{w_{st}}\right)^{1-\mu_i}\right]^{\frac{\varepsilon_i-\mu_i}{\mu_i-1}}. \tag{36}$$

certain values of μ_e and μ_m as a response to an increase in z_{ket} or z_{set}. Third, higher values of ε_e are less likely to amplify the long-run output impact when productivity shocks result from unskilled-biased technical change. Finally, since all these productivity shocks are sector specific, the impact will be stronger in the sector experiencing the greatest productivity increase.

Short-Run Effects

Let us now analyze the short-run effects for which Eq. (34) is now relevant. The maximization problem that determines the optimal investment in physical capital is

$$\max_{x_{it}} \left\{ p_i \Omega_{it} z_{kit} k_{it} - R \sum_{j=1}^{t} (1-\delta)^{t-j} x_{ij} - w_{nt} n_{it} - w_{st} s_{it} \right\} \tag{37}$$

subject to the motion of capital, which is determined by Eq. (3), and the constant input proportion conditions given by Eqs. (29) and (30). Solving this problems delivers the same solution as the benchmark model, given by Eq. (20), but now $\Psi_{it} = p_i \Omega_{it} - \frac{w_{nt}}{\omega_{it} z_{nit}} - \frac{w_{st}}{\theta_{it} z_{sit}}$. Therefore, following the same logic as in the proof of Proposition 3 in Appendix A, we can focus on the particular case where capital adjustment costs are so strong (i.e., ϕ sufficiently small) that the change in the capital input is negligible. In this scenario, $\Omega_{it} z_{kit}$ gives the response of short-run output to productivity shocks.

From Eqs. (29), (30), and (35), when z_{kit} increases, both θ_{it} and ω_{it} increase, pushing Ω_{it} down. This implies that both skilled and unskilled labor decrease per unit of capital. Therefore, as in the benchmark model, capital-augmenting productivity shocks can reduce output in the short run if the decrease in Ω_{it} in absolute value is larger than the increase in z_{kit}.

Skill-biased technical change, on the other hand, is less likely—though not impossible—to cause a decrease in short-run output. As z_{sit} rises, ω_{it} increases, but θ_{it} falls, making the overall impact on Ω_{it} uncertain. This occurs because, while the amount of unskilled labor per unit of capital falls, the amount of skilled labor increases. Finally, in the short run, the impact of z_{nit} on sector i's output can only be positive—note that as z_{nit} rises, ω_{it} decreases, θ_{it} does not vary, and then Ω_{it} increases.

We also aim to examine how input elasticities affect the strength of a potential negative short-run effect on output. Therefore, we focus on how the impact of z_{ket} and z_{set} varies with ε_e and μ_e. As ε_e increases, $\frac{\partial \theta_{et}}{\partial z_{ket}}$ remains unchanged, but $\frac{\partial \omega_{et}}{\partial z_{ket}}$ increases, potentially strengthening the negative effect on short-run output. The influence of ε_e on the short-run impact of z_{set} is qualitatively identical to that of z_{ket}.

Conversely, an increase in μ_e, raises $\frac{\partial \theta_{et}}{\partial z_{ket}}$ but decreases $\frac{\partial \omega_{et}}{\partial z_{ket}}$, thus implying that the influence of μ_e on the short-run response to a z_{kit} shock is ambiguous. In contrast, μ_e has a well-defined impact on input proportion responses to changes in z_{sit}. When μ_e increases, $\frac{\partial \theta_{et}}{\partial z_{set}}$ becomes more negative and $\frac{\partial \omega_{et}}{\partial z_{set}}$ less positive, making a positive effect of z_{sit} on short-run output more likely.

We can summarize the short-run results when there are strong adjustment costs for the capital input as follows. First, capital-biased productivity shocks can negatively affect sec-

toral output in the short run. Furthermore, as in the benchmark model, for certain values of ε_e and ε_m, an increase in ε_e can amplify this negative short-run impact. The influence of μ_e is less clear, as it affects the capital-unskilled-labor and the capital-skilled-labor ratios in opposite directions. Second, skilled-biased technical change is less likely to generate short-run output losses due to the increase in the amount of skilled labor. Third, unskilled-biased technical change cannot reduce output in the short run. Finally, since productivity shocks are sector-specific, all these effects will be more pronounce if productivity gains impact the extractive industry more significantly.

D. Estimating ESKL and the Productivity Parameters

We introduce time and sector subindices when necessary to allow R, w_t and ε_i to vary across time and sectors. Hence, Eqs. (2) and (10) become

$$y_{et} = \left[(z_{kt} k_{et})^{1-1/\varepsilon_{et}} + (z_{nt} n_{et})^{1-1/\varepsilon_{et}} \right]^{\frac{\varepsilon_{et}}{\varepsilon_{et}-1}}, \tag{38}$$

$$\frac{k_{et}}{n_{et}} = \left(\frac{z_{kt}}{z_{nt}} \right)^{\varepsilon_{et}-1} \left(\frac{w_{et}}{R_{et}} \right)^{\varepsilon_{et}}, \tag{39}$$

$$y_{mt} = \left[(z_{kt} k_{mt})^{1-1/\varepsilon_{mt}} + (z_{nt} n_{mt})^{1-1/\varepsilon_{mt}} \right]^{\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}}, \tag{40}$$

$$\frac{k_{mt}}{n_{mt}} = \left(\frac{z_{kt}}{z_{nt}} \right)^{\varepsilon_{mt}-1} \left(\frac{w_{mt}}{R_{mt}} \right)^{\varepsilon_{mt}}. \tag{41}$$

We can use these to obtain

$$z_{nt} = \frac{y_{it}}{n_{it}} \left(\frac{w_{it} n_{it}}{p_{it} y_{it}} \right)^{\frac{\varepsilon_{it}}{\varepsilon_{it}-1}}, \quad \text{for } i = e, m, \tag{42}$$

and

$$z_{kt} = \frac{y_{it}}{k_{it}} \left(\frac{R_{it} k_{it}}{p_{it} y_{it}} \right)^{\frac{\varepsilon_{it}}{\varepsilon_{it}-1}}, \quad \text{for } i = e, m. \tag{43}$$

Finally, equalizing Eqs. (42) and (43) across the two sectors delivers

$$\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1} = \frac{\ln\left(\frac{y_{mt}/k_{mt}}{y_{et}/k_{et}}\right) - \frac{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}{\ln\left(\frac{w_{et}n_{et}}{p_{et}y_{et}}\right)} \ln\left(\frac{y_{mt}/n_{mt}}{y_{et}/n_{et}}\right)}{\frac{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}{\ln\left(\frac{w_{et}n_{et}}{p_{et}y_{et}}\right)} \ln\left(\frac{w_{mt}n_{mt}}{y_{mt}}\right) - \ln\left(\frac{R_{mt}k_{mt}}{p_{mt}y_{mt}}\right)} \tag{44}$$

and

$$\frac{\varepsilon_{et}}{\varepsilon_{et}-1}=\frac{\ln\left(\frac{y_{mt}/k_{mt}}{y_{et}/k_{et}}\right)+\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}\ln\left(\frac{R_{mt}k_{mt}}{p_{mt}y_{mt}}\right)}{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}. \tag{45}$$

Using data for y_{et}, y_{mt}, k_{et}, k_{mt}, n_{et}, n_{mt}, w_{et}, w_{mt}, R_{et} and R_{mt}, we can thus obtain an estimate of ε_{mt} from Eq. (44). Then, taking ε_{mt} into Eq. (45) gives ε_{et}. Finally, substituting ε_{mt} and ε_{et} into (42) and (43) gives z_{nt} and z_{kt}. We can thus obtain the ESKL for each of the two sectors and the common labor-augmenting and capital-augmenting productivities, at any given point in time.

More specifically, the EUKLEMS provides data for the variables required to perform the estimation. Output variables y_{et} and y_{mt}, and the stocks k_{et}, k_{mt}, n_{et} and n_{mt} are directly available in the dataset. We compute the salaries w_{et} and w_{mt} by dividing total labor compensations by total hours worked (n_{it}). We compute R_{et} and R_{mt} by dividing total capital compensations by the total capital stock (k_{it}). This is consistent, for example, with the computations undertaken by Caselli and Coleman (Caselli et al. 2006).

E. Data

We use an annual state-level panel that, unless otherwise specified, covers the 48 continental U.S. states for the period 1963–2015. Real variables are expressed in 2009 prices. Descriptive statistics for all variables are presented in Table A1.

Table A1 Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
Gross State Product (per capita)	24132.97	17654.36	1971.93	83245.73
Unemployment rate	0.06	0.02	0.02	0.18
Capital stock (per capita)	39491.51	35297.49	9001.79	435258.61
Population (1000s)	4826.11	5278.32	256	36580
Tax revenues (per capita)	13959.86	12447.50	668.13	126924.21
Government expenditures (per capita)	12014.96	9747.07	592.12	58813.42
Resource endowment	0.002	0.006	0	0.081
Government debt (per capita)	1783.42	1989.69	12.86	12790.27
Party affiliation of governor	0.44	0.49	0	1
Inequality	0.61	0.23	0.27	1.49
Fernald TFP shocks (utility adjusted)	1.009	1.372	-2.560	3.491
Zk	0.097	0.087	0.013	0.315
Zn	0.388	0.075	0.253	0.534
JPT TFP shocks	0.017	0.412	-1.046	1.198
BS TFP shocks	-0.003	0.530	-1.411	1.661
FORD TFP shocks	0.015	0.492	-1.039	1.173
Federal tax shocks	-0.400	1.549	-7.277	2.455
Monetary shocks	0	0.972	-2.416	2.016
IST news shocks	0.091	0.798	-1.957	1.906
Business Cycles	0.117	0.277	0	1
GSP share of manufacturing	0.095	0.042	0.019	0.215
GSP share of services	0.149	0.011	0.121	0.341
GSP share of agriculture	0.003	0.003	0	0.014
GSP share of wholesale	0.053	0.004	0.046	0.069

Notes: See Appendix for detailed description of variables.

Variable definitions

Resource endowment: Recoverable state stocks of oil and natural gas (cross-sectional), normalized by average state income (averaged over 1958–2008). Alaska and Hawaii are excluded. Source: James (2015)

Real per-capita Gross State Product (GSP): Real Gross State Product divided by state population. Source: U.S. Census Bureau.

Population: State population. Source: U.S. Census Bureau.

Real per-capita tax rates: State tax revenues divided by state population. Source: U.S. Census Bureau.

Real per-capita government expenditures: Total expenditures of state government divided by state population. Source: U.S. Census Bureau.

Real per-capita state outstanding debt: Total outstanding debt of state government divided by state population. Source: U.S. Census Bureau.

Party affiliation of governor: An indicator for the party of the governor; 0 = Republican, 1 = Democrat, 0.5 = non-major party governor. Source: Marty and Grossman (2016).

Inequality: Theil Index measure of income inequality. Source: Frank (2009).

Unemployment rate: State unemployment rate. Source: U.S. Census Bureau.

Real per-capita capital stock: State capital stock divided by state population. Source: Garofalo and Yamarik (2002), including an extension of it available at the second author's homepage.

Fernald TFP shocks: Aggregate, national TFP shocks, aggregated to an annual level. Source: Fernald (2014).

Federal tax shocks: Narrative-based federal tax shocks, aggregated to an annual level, and normalized by U.S. GDP; available up to 2007. Source: Romer and Romer (2010).

Business cycles: An indicator for whether the U.S. economy is in a recession. Source: U.S. Federal Reserve.

News shocks: Investment Specific Technology (IST) news shocks, aggregated to an annual level; available up to 2011. Source: Ben-Zeev (2018).

Monetary shocks: Monetary policy shocks a-la Romer and Romer (2004); available for 1969–2007. Source: Tenreyro and Thwaites (2016).

JPT TFP shocks: Series of TFP shocks derived from Justiniano et al. (2011).

BS TFP shocks: Series of TFP news shocks derived from Barsky and Sims (2011).

FORD TFP shocks: Series of TFP shocks derived from Francis et al. (2014).

Zk: Capital-augmenting technology shocks. Computed from the model, as described in the text, vis-à-vis data from the EUKLEMS dataset. Source: O'Mahony and Timmer (2009).

Zn: Labor-augmented technology shocks. Computed from the model, as described in the text, vis-à-vis data from the EUKLEMS dataset. Source: O'Mahony and Timmer (2009).

GSP share of manufacturing: Share of state manufacturing sector in Gross State Product. Source: U.S. Census Bureau.

GSP share of services: Share of state services sector in Gross State Product. Source: U.S. Census Bureau.

GSP share of agriculture: Share of state agriculture sector in Gross State Product. Source: U.S. Census Bureau.

GSP share of wholesale: Share of state wholesale trade sector in Gross State Product. Source: U.S. Census Bureau.

F. VAR analysis

In Sect. 4.7 of the paper, we have examined the dynamic patterns following the method of local projections (Jorda 2005). To examine the robustness of the observed patterns to the type of estimation method, we undertake an equivalent estimation under a VAR framework.

Specifically, we estimate

$$\Delta(outcome)_{i,\Delta(t-1,t)} = \alpha + \beta(outcome)_{i,t-1} + \gamma(resource)_i + \delta(tfp)_t + \sum_{j=0}^{j=4} \theta_j (resource * tfp)_{i,t-j} + \eta_i + \nu_t + \epsilon_{i,t}. \quad (46)$$

Here $outcome$ again denotes each of the three outcome variables. The results are presented in Table A2. Columns (1)-(3) examine the cases of GSP, unemployment, and capital, respectively. The observed patterns are qualitatively similar to those under the Jorda (2005) method outlined in Sect. 4.7. We note that upon impact, TFP shocks contract output and labor more strongly in resource-rich than resource-poor states, but there are no such differential impacts on capital. However, specifically from about the second or third years, output, labor, and capital expand more strongly in those same, initially contracted, resource-rich states. These results indicate that the main observed patterns are robust to this alternative estimation method.

Table A2 Resource endowments and technology improvements (VAR analysis)

	(1)	(2)	(3)
Dependent variable:	GSP	Unemployment	Investment
Resources X TFP	-0.96***	0.65***	0.08
	(0.17)	(0.22)	(0.07)
Resources X TFP (t-1)	-0.38***	0.77***	0.03
	(0.11)	(0.25)	(0.06)
Resources X TFP (t-2)	0.12***	-1.79***	0.12
	(0.04)	(0.64)	(0.08)
Resources X TFP (t-3)	0.72***	-2.98***	0.4**
	(0.12)	(0.93)	(0.16)
Resources X TFP (t-4)	0.94***	-3.3***	0.04**
	(0.12)	(1.11)	(0.02)
Resources X TFP (t-5)	0.66***	-2.87**	0.07***
	(0.21)	(1.29)	(0.01)
State fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R-squared	0.88	0.69	0.91
Observations	2260	1640	2260

Notes: Standard errors are robust, clustered by state, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance. The dependent variable is real per capita Gross State Product (Column 1), the unemployment rate (Column 2), and real per capita investment (Column 3), each in natural logarithm. All regressions include an intercept, and lagged dependent variable. The sample includes the 48 continental U.S. states and covers the period of 1963-2015. 'Resources' denotes the resource endowment measure described in the text. 'TFP' denotes the Fernald series of purified technology changes (Fernald (2014)). For further information on variables see data Appendix.

Funding Open access funding provided by Hebrew University of Jerusalem. Open access funding provided by Hebrew University of Jerusalem. Fidel Perez Sebastian acknowledges funding from the Spanish Ministry of Science and Innovation, Projects PID 2019-111208 GB-I00 and PID2023-153032NB-I00.

Data availability The data used in this study is available from the authors upon request.

Declarations

Conflict of Interest The authors have no conflicts of interest to disclose.

References

Acemoglu D (2002) Technical change, inequality and the labor market. J Econ Lit 40:7–72

Allcott H, Keniston D (2018) Dutch disease or agglomeration? the local economic effects of natural resource booms in modern America. Rev Econ Stud 85(2):596–731
Antras P (2004) Is the u.S. aggregate production function cobb-douglas? new estimates of the elasticity of substitution. Contrib Macroecon 4(1):20121005
Arezki R, Ramey AV, Sheng L (2017) News shocks in open economies: evidence from giant oil discoveries. Q J Econ 132(1):103–155
Armand A, Coutts A, Vicente P, and Vilela I (2020) Does information break the political resource curse? experimental evidence from Mozambique. The Am Econ Rev 110(11):3431–3453
Balistreri EJ, McDaniel CA, Wong EV (2003) An estimation of u.S. industry-level capital–labor substitution elasticities: support for cobb–douglas. N Am J Econ Finance 14(3):343–356
Barsky RB, Sims ER (2011) News shocks and business cycles. J Monet Econ 58(3):273–289
Basu S, Fernald GJ, Kimball SM (2006) Are technology improvements contractionary? The Am Econ Rev 96:1418–1448
Ben-Zeev N (2018) What can we learn about news shocks from the late 1990s and early 2000s boom-bust period? J Econ Dyn Control 87:94–105
Bhattacharyya S, Hodler R (2010) Natural resources, democracy and corruption. Eur Econ Rev 54(4):608–621
Bils M (1998) Discussion of technology and business cycles: how well do standard models explain the facts? In Federal Reserve Bank of Boson Conference Series 42, What Causes Business Cycles, Beyond Shocks, 255–263.
Brollo F, Nannicini T, Perotti R, Tabellini G (2013) The political resource curse. The Am Econ Rev 103(5):1759–1796
Caballero RJ (1994) Small sample bias and adjustment costs. Rev Econ Stat 52–58
Caballero RJ, Engel EM, Haltiwanger JC, Woodford M, Hall RE (1995) Plant-level adjustment and aggregate investment dynamics. Brookings papers on economic activity, 1–54
Caliendo L, Parro F, Rossi-Hansberg E, Sarte P-D (2018) The impact of regional and sectoral productivity changes on the us economy. Rev Econ Stud 85(4):2042–2096
Cantore C, León-Ledesma M, McAdam P, Willman A (2014) Shocking stuff: technology, hours, and factor substitution. J Eur Econ Assoc 12(1):108–128
Caselli F, Coleman, Wilbur John I (2006) The world technology frontier. The Am Econ Rev 96(3):499–522
Chang Y, Hong JH (2006) Do technological improvements in the manufacturing sector raise or lower employment? The Am Econ Rev 96(1):352–368
Chirinko RS (2008) σ: the long and short of it. J Macroecon 30(2):671–686
Christiano LJ, Eichenbaum M, Vigfusson R (2004) The response of hours to a technology shock: evidence based on direct measures of technology. J Eur Econ Assoc 2(2–3):381–395
Doraszelski U, Jaumandreu J (2013) R&d and productivity: estimating endogenous productivity. Rev Econ Stud 80(4):1338–1383
Duffy J, Papageorgiou C, Perez-Sebastian F (2004) Capital-skill complementarity? evidence from a panel of countries. Rev Econ Stat 86:327–344
Escribá-Pérez FJ, Murgui-García MJ, Ruiz-Tamarit JR (2023) Endogenous capital stock and depreciation in the United States. J Public Econ Theory 25(1):139–167
Fernald J (2014) A quarterly, utilization-adjusted series on total factor productivity, Federal Reserve Bank of San Francisco Working Paper 2012-19
Francis N, Owyang MT, Roush JE, DiCecio R (2014) A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks. Rev Econ Stat 96(4):638–647
Francis N, Ramey VA (2005) Is the technology-driven real business cycle hypothesis dead? shocks and aggregate fluctuations revisited. J Monet Econ 52:1379–1399
Frank MW (2009) Inequality and growth in the United States: evidence from a new state-level panel of income inequality measures. Econ Inq 47(1):55–68
Gali J (1999) Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations? The Am Econ Rev 89(1):249–271
Garofalo G, Yamarik S (2002) Regional convergence: evidence from a new state-by-state capital stock series. Rev Econ Stat 84:316–323
Groth C, Khan H (2010) Investment adjustment costs: an empirical assessment. J Money Credit Bank 42(8):1469–1494
Gylfason T (2001) Natural resources, education and economic development. Eur Econ Rev 4:847–859
Gylfason T, Herbertsson TT, Zoega G (1999) A mixed blessing: natural resources and economic growth. Macroecon Dyn 3(2):204–225
Hicks JR (1932) The theory of wages. Macmillan and Co, London
James A (2015) U.S. state fiscal policy and natural resources. Am Econ J Econ Policy 7(3):238–257
James A, Rivera NM (2022) Oil, politics, and corrupt bastards. J Environ Econ Manag 111:102599

James A, Smith B (2017) There will be blood: crime rates in shale-rich u.S. counties. J Environ Econ Manag 84:125–152
Jorda O (2005) Estimation and inference of impulse responses by local projections. The Am Econ Rev 95:161–182
Justiniano A, Primiceri GE, Tambalotti A (2011) Investment shocks and the relative price of investment. Rev Econ Dyn 14(1):102–121. Special issue: Sources of Business Cycles.
Klump R, McAdam P, Willman A (2007) Factor substitution and factor-augmenting technical progress in the u.S.: a normalized supply-side system approach. Rev Econ Stat 89(1):183–192
Krugman P (1987) The narrow moving band, the Dutch disease, and the competitive consequences of mrs. thatcher: notes on trade in the presence of dynamic scale economies. J Dev Econ 27(1–2):41–55
Krusell P, Ohanian LE, Ríos-Rull J-V, Violante GL (2000) Capital-skill complementarity and inequality: a macroeconomic analysis. Econometrica 68(5):1029–1053
Kuralbayeva K, Stefanski R (2013) Windfalls, structural transformation and specialization. J Int Econ 90(2):273–301
Kydland FE, Prescott EC (1982, 1345–1370) Time to build and aggregate fluctuations. Econometrica
León-Ledesma MA, McAdam P, Willman A (2010) Identifying the elasticity of substitution with biased technical change. The Am Econ Rev 100(4):1330–1357
Liu C, Williams N (2019) State-level implications of federal tax policies. J Monet Econ 105:74–90
Marty J, Grossman M (2016) The correlates of state policy project v.1.10. Institute for Public Policy and Social Research (IPPSR), East Lansing, MI
Michaels G (2011) The long term consequences of resource-based specialisation. The Econ J 121(551):31–57
Michaels G, Natraj A, Van Reenen J (2014) Has ict polarized skill demand? evidence from eleven countries over 25 years. Rev Econ Stat 96(1):60–77
O'Mahony M, Timmer MP (2009) Output, input and productivity measures at the industry level: the euklems database. The Econ J 119(538):F374–F403
Perez-Sebastian F, Raveh O (2019) Federal tax policies, congressional voting, and natural resources. Can J Econ 52(3):1112–1164
Perez-Sebastian F, Raveh O, Reingewertz Y (2019) Heterogeneous vertical tax externalities and macroeconomic effects of federal tax changes: the role of fiscal advantage. J Urban Econ 112:85–110
Raval DR (2019) The micro elasticity of substitution and non-neutral technology. The RAND J Econ 50(1):147–167
Raveh O (2013) Dutch disease, factor mobility, and the alberta effect - the case of federations. Can J Econ 46(4):1317–1350
Raveh O (2020) Monetary policy, natural resources, and federal redistribution. Environ Resour Econ 75:585–613
Raveh O, Reshef A (2016) Capital imports composition, complementarities, and the skill premium in developing countries. J Dev Econ 118:183–206
Romer DC, Romer HD (2004) A new measure of monetary shocks: derivation and implications. The Am Econ Rev 94(4):1055–1084
Romer DC, Romer HD (2010) The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. The Am Econ Rev 100:763–801
Sachs JD, Warner AM (2001) The curse of natural resources. Eur Econ Rev 45(4–6):827–838
Satō K (1975) Production functions and aggregation, Vol 90
Stijns J-P (2006) Natural resource abundance and human capital accumulation. World Dev 34(6):1060–1083
Tenreyro S, Thwaites G (2016) Pushing on a string: us monetary policy is less powerful in recessions. Am Econ J Macroecon 8(4):43–74
Tornell A, Lane P (1999) The voracity effect. The Am Econ Rev 89:22–46
Torvik R (2001) Learning by doing and the Dutch disease. Eur Econ Rev 45(2):285–306
Torvik R (2002) Natural resources, rent seeking and welfare. J Dev Econ 67(2):455–470
Van der Ploeg F (2011) Natural resources: curse or blessing? J Econ Lit 49(2):366–420
Van der Ploeg F, Poelhekke S (2016) The impact of natural resources: survey of recent quantitative evidence. J Devel Stud 53(2):205–216
Van Wijnbergen S (1984) The Dutch disease: a disease after all. The Econ J 194:41–55
Venables A (2016) Using natural resources for development: why has it proven so difficult? J Econ Perspectives 30:161–184
Violante GL (2008) Skill-biased technical change. In: Durlauf SN, Blume LE (eds) The new palgrave dictionary of economics, vol 2. Palgrave Macmillan, London, pp 1–6
Young AT (2013) U.S. elasticities of substitution and factor augmentation at the industry level. Macroecon Dyn 17(4):861–897

Authors and Affiliations

Fidel Perez-Sebastian[1] · Ohad Raveh[2] · Frederick van der Ploeg[3,4,5,6]

✉ Ohad Raveh
ohad.raveh@mail.huji.ac.il

Fidel Perez-Sebastian
fidel.perez@ua.es

Frederick van der Ploeg
rick.vanderploeg@economics.ox.ac.uk

1 Department of Economics, University of Alicante, Alicante, Spain

2 Department of Environmental Economics and Management, Hebrew University of Jerusalem, Jerusalem, Israel

3 Department of Economics, University of Oxford, Oxford, UK

4 Department of Economics, Uiversity of Amsterdam, Amsterdam, Netherlands

5 CEPR, London, UK

6 CESifo, Munich, Germany