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Abstract

Are technology improvements contractionary? We re-examine this central question, accounting for the presence of natural resources. A two-sector model of economic growth 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 our analytical 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 labor and capital across the natural resources dimension. Second, we find that an increase in TFP is on impact contractionary in resource-rich states, yet 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.

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1 Introduction

Are technology improvements contractionary? Studies on the contemporaneous impacts of technological shocks suggests that the jury is still out. While standard frictionless Real Business Cycle models predict short-term expansionary effects, other canonical macro workhorse models predict the opposite.[1] We re-examine this central question, theoretically and empirically, accounting for the presence of natural resources. Understanding the nexus between natural resources and economic growth has been of perennial interest to economists and policy makers.[2] The literature has highlighted a host of potential transmission channels, including Total Factor Productivity (TFP) and innovation.[3] Little attention, however, has been given to the potential role of resource abundance in transmitting the impacts of technological change on the economy.

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. We find that the contractionary impacts of TFP shocks are observed primarily in resource-rich areas, in a robust and economically meaningful magnitude, and are non-apparent or even expansionary, elsewhere. Our results offer one possible reconciliation for the ongoing debate over the opposing contemporaneous effects of TFP shocks on the economy, and shed light on previously overlooked potential adverse effects of natural resource abundance.

The notion that the oil and gas sectors tend to be relatively abundant 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 (Duffy et al., 2004; Krusell et al., 2000; Raveh and Reshef, 2016) then suggests that the elasticity of substitution between capital and labor should be relatively higher in resource-rich sectors. This prediction has been substantiated in a number of cross-sectional studies.[4] Raveh (2020) illustrates that these features may translate to the macroeconomic level in economies with a dominant oil and gas sector and that they may persist over time, 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 elasticities between capital and labor; positing, and later documenting empirically,

[1] See, e.g., Chang and Hong (2006). The inconclusive, ongoing debate over this issue is further summarized in the following section.

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

[3] The literature, reviewed in more detail in the next section, unveils the potential endogeneity of TFP shocks and innovation to resource abundance and windfalls through various underlying mechanisms that range from decreased factor productivity (e.g., Kuralbayeva and Stefanski, 2013) to crowding out of entrepreneurial endeavors (e.g., Torvik, 2002).

[4] See, e.g., Caballero et al. (1995) and Young (2013). We review the related literature in the next section.

that they are persistently higher in extractive industries than in other sectors. Importantly, the underlying production in resource-rich sectors is based on geological features, rendering the consequent persistent elasticity and capital intensity differences plausibly exogenous.

Notably, the relative size of input substitution elasticities is, as we later illustrate theoretically, central to understanding the contemporaneous impact of technological changes on growth.[5] The intuition is simple: a positive technology shock may on the one hand increase the productivity of capital, yet on the other hand may reduce the need for labor, via factor substitution. The latter may be either an indirect result of labor-substituting capital formation, or a direct one of technological improvements that replace labor. In an environment with highly elastic factor substitution, the increase in capital productivity may not compensate for the decrease in labor output, and total production may fall. Yet, if substitution between factor inputs is weak, technological improvements may be expansionary also in the short-term. Conversely, in the long-term, under full employment, technological improvements would be expansionary irrespective of the ease of factor substitution, and more so in cases with an initially high capital-labor ratio which benefit most from increases in capital productivity.

We thus conjecture that due to differences in capital intensities and factor substitution elasticities, TFP shocks may contract economies that are rich in natural resources in the short-term, yet be non-contractionary or even expansionary in resource-poor ones. In the long-term, however, they may give rise to relatively stronger expansionary impacts in those, initially contracted, resource-rich economies. 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. This model serves two purposes. First, we employ it to derive sector elasticities and capital- and labor-augmenting technology shocks over time using U.S. industry-level data. Second, we consider sectoral differences in the extent of capital intensity and factor substitution elasticities, and analyze the short- and long-term equilibrium effects of technology shocks.

Our model-driven calculations are based on U.S. industry data for the period 1998-2015 and are derived from the EUKLEMS dataset (O'Mahony and Timmer, 2009). This dataset provides measures for the key model parameters, and hence enables us to compute time-series data for the remaining parameters related to capital- and labor-augmenting technology shocks, and factor substitution elasticities across sectors, focusing on the extractive (mining and quarrying) industry versus a weighted average of the remaining ones. Computing these parameters directly from a model has the merit compared to other methods (e.g., estimation of translog equations)

[5]The notion that the elasticity of substitution parameter is central for understanding the impacts of technological changes dates back to Hicks (1932), and Satō (1975).

as it enables us to disentangle the technological shocks, via existing time-series data, and study their impact over time, as well as estimate time-varying elasticity parameters across the sample period. The results indicate that the average elasticity in the extractive case is 0.79, i.e., below 1, but higher than the estimate of the average elasticity of 0.55 for the non-extractive case. These are in line with those found before (e.g., Chirinko, 2008).

Translating the outlined cross-industry differences in capital abundance and elasticities to the model, our analytical results indicate that while labor-augmenting technological improvements are similarly expansionary in both sectors, over the short and long terms, the patterns are different for capital-augmenting ones, as unlike the former, they affect the effective-input ratio. Specifically, a capital-augmenting technology shock increases the productivity of capital while substituting labor, thus giving rise to involuntary unemployment in the short-run. Capital adjustment costs, in turn, induce a gradual convergence back to full employment. Our analysis indicates that in the short-term the impact is contractionary if the elasticity of substitution between labor and capital is sufficiently high. However, in the long-term the magnitude of the expansion depends on the initial capital-intensity level, thus pointing at the potential divergent outcome across resource-rich and -poor economies.

Our predictions are corroborated by our empirical results. We undertake an empirical investigation of the effect of national TFP shocks on output and inputs across levels of resource intensities via a U.S. state-level analysis (complemented by a county-level analysis for robustness). An intra-U.S. perspective is appealing for our purposes because it provides ample cross-state variation in geologically-based natural endowments of crude oil and natural gas that are locally impactful, as well as in additional economic indicators. In addition, it does so under a relatively homogeneous environment in which economies are not large enough to alter the course of national technological trends, including importantly through the extent of their natural resource wealth.[6]

Our analysis is based on two main measures: national technology shocks, and state resource wealth. For the former we employ the purified utility-adjusted U.S. TFP series of Basu et al. (2006) (henceforth, BFK), aggregated to an annual level. Besides representing a standard measure, it is also useful for comparing our analysis directly to BFK, which we conduct before our core empirical analysis. As for natural resource wealth, we consider the cross-sectional geologically-based measure of recoverable stocks of oil and gas, aggregated to the state-level via data from the U.S. Geological Survey, developed by James (2015). We outline further characteristics of these measures in the empirical section.

[6]We do, however, provide robustness tests for the exclusion of the largest states, as well as for the exclusion of those with the largest resource endowments, and for those with none.

To that end, we have assembled an annual-based panel of the 48 continental U.S. states over the period 1963-2015.[7] Our identification strategy rests on the plausibly exogenous cross-sectional and temporal variations induced by the interaction of the two main measures, namely TFP and natural resources, driven by the geological roots of natural endowments and the notion that states take national technological trends as given. In particular, our setting considers national technology changes, exogenous to state resource wealth and other indicators, and interacts these with cross-sectional state resource endowments. This enables us to examine the impacts of TFP shocks on growth, and how these are affected by differences in natural resource intensities.[8] Our starting point in the analysis is BFK. We examine our main hypothesis under their framework and time period. Thereafter, turning to our core analysis with the complete sample, we test the contemporaneous effect of the interaction of our two measures of interest on state output, investment, and unemployment, using a panel fixed-effects framework. Last, we examine the long-term impacts by estimating impulse responses, for each of the outcome variables, following the method of local projections of Jorda (2005).

We find that if natural resources are abundant, technology improvements, most notably capital-augmenting ones, have a contemporaneously contractionary effect, driven by labor market impacts. Conversely, if natural resources are less abundant, the same improvements are not contractionary at worst, and expansionary at best. Our baseline estimates indicate that a one standard deviation increase in TFP contracts average output of resource-rich states by 0.1% relative to the output of resource-poor states. In addition, we find that two to five years ahead, a positive technology shock expands output and inputs in resource-rich economies more strongly than in their resource-poor counterparts.

These patterns are consistent with our analytical predictions. Moreover, they are observed under the BFK framework and period, and are robust to various tests. First, we show that they are specific to differences in natural resource endowments, rather than in various other major sectors. Second, we illustrate that they are observable also at the county level, and are robust to using different measures of the main variables. Last, we show that these patterns are robust to considering different sample restrictions, specifications, and controls.

Section 2 reviews related literature and places our contributions within it. Section 3 explains analytically how the impact of technology shocks depends on the degree of resource abundance. Section 4 presents the data, empirical findings, and robustness tests. Section 5 concludes.

[7] The cross-sectional and time coverage are restricted by the availability of the various measures employed in the analysis.

[8] 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 Perez-Sebastian et al. (2019), Liu and Williams (2019), and Raveh (2020), among others.

2 Related Literature

Our contributions are related to three strands of literature. First, economists have long noticed that natural resource abundance can turn out to be a blessing as well as a curse.[9] A central aspect is the potential negative impact of resource abundance on productivity and innovation. Among the various channels proposed, 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 specialization that crowds out innovation and entrepreneurship (e.g., Michaels, 2011; Kuralbayeva and Stefanski, 2013; 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 has taken a central role in the macroeconomic literature. While standard frictionless Real Business Cycle models predict that technology improvements are expansionary in the short-term, sticky-price models predict the opposite. The related empirical literature is also inconclusive. For instance, in their seminal work BFK have shown that technology improvements are contractionary on impact due to decreases in input use, most notably labor. However, Christiano et al. (2004) have shown that their correction of the BFK technology measure yields contemporaneously expansionary effects, focusing on labor.

Our aim is to offer a potential reconciliation of the opposing views based on the role of natural resources and the underlying persistent differences in elasticities of substitution between labor and capital. We observe that the short-term impacts of technology improvements are contractionary primarily in resource-rich areas, 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). Last, 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.

[9] 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.

Third, there is no shortage of studies that provide estimates for the aggregate elasticity of substitution between capital and labor (e.g., Doraszelski and Jaumandreu, 2013; Klump et al., 2007; Raval, 2019). The evidence summarized in Chirinko (2008) point at estimates well below 1. 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.[10] Nonetheless, these are cross-sectional estimates that refer to a specific point in time, or an average over various periods.

Conversely, we estimate time series for the elasticities of substitution between labor and capital for the oil sector, and compare it to the time series for the average elasticities for the remaining economy, over time. We do so by employing U.S. industry data to compute the elasticity parameter directly from our analytical framework. This method enables us to estimate the substitution elasticities over time. We do this for CES prduction functions and non-neutral productivity shocks, which are essential for the estimation of elasticities (Antras, 2004). While the average estimates are below one, consistent with previous estimates, we document persistent differences across sectors over time: the elasticities of substitution between labor and capital estimated for the extractive industry is significantly and consistently higher than the corresponding elasticities for an average of the remaining economy.

3 Effects of technology shocks in a two-sector economy

Here we analyze the implications of cross-sector differences in the elasticity of substitution between labor and capital for the short- and long-term impacts of productivity shocks. Following Caballero (1994) and BFK, our framework features investment adjustment costs.

3.1 Short-run effects of technology shocks

Consider an economy with two production sectors: extractive (e) and the non-extractive (m). The economy is inhabited by a constant population of N individuals that are endowed with one unit of labor that is supplied inelastically. We suppose that capital and output markets are open and that we have a small open economy. The prices of these goods are then determined

[10]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).

on world market. There is no immigration or emigration of labor, so that the labor market is closed.

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 Leontief production function,

$$y_{it} = \Omega_i \min \{z_k k_{it}, \omega_i z_n n_{it}\}, \tag{1}$$

where y_{it} represents output in sector i at period t, Ω_i is a productivity parameter specific to sector i, ω_i controls the proportions in which capital and labor enter production, and z_k and z_n provide productivity levels specific to capital and labor, respectively.

New technologies bring labor-augmenting gains when z_n rises, and capital-augmenting technical progress when z_k rises. The new vintages also come with particular values of ω_i and Ω_i. These result from the long-run, sector-specific elasticity of substitution between capital and labor (ε_i) not being equal zero. In the long-run, the production function takes the CES form,

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

Denote by k_i^* and n_i^* the long-run levels of productive capital and labor for a given vintage. Then, the values of ω_i and Ω_i are implied by the solution to

$$\max_{\{k_i^*, n_i^*\}} \left\{ p_i \left[(z_k k_i^*)^{1-1/\varepsilon_i} + (z_n n_i^*)^{1-1/\varepsilon_i}\right]^{\frac{\varepsilon_i}{\varepsilon_i - 1}} - R k_i^* - w n_i^* \right\}, \tag{3}$$

where p_i is the price of output in sector i, R represents the gross return to capital (i.e., the interest rate plus the depreciation rate), and w the wage rate. For simplicity, problem (3) assumes zero investment adjustment costs to obtain the long-run values of the inputs. In addition, since we consider the non-extractive industry as the numeraire and the prices of output, $p_m = 1$ while p_e, and the gross return, R, are constant and given on world markets. The first-order optimality conditions for capital and labor are

$$p_i z_k \left[z_k^{1-1/\varepsilon_i} + \left(\frac{z_n n_i^*}{k_i^*}\right)^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1} - 1} = R, \tag{4}$$

$$p_i z_n \left[\left(\frac{z_k k_i^*}{n_i^*}\right)^{1-1/\varepsilon_i} + z_n^{1-1/\varepsilon_i} \right]^{\frac{\varepsilon_i}{\varepsilon_i - 1} - 1} = w. \tag{5}$$

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

$$\omega_i \equiv \frac{z_k k_i^*}{z_n n_i^*} = \left(\frac{z_k}{z_n} \frac{w}{R} \right)^{\varepsilon_i}. \tag{6}$$

Notice that the definition of ω_i guarantees that $n_{it} = n_i^*$ in the long-run.

Equations (5) and (6) for the non-extractive industry give the factor price frontier,

$$w = z_n \left(1 - z_k^{\varepsilon_m - 1} R^{1-\varepsilon_m} \right)^{1/(1-\varepsilon_m)}. \tag{7}$$

The wage rate, w, increases in the productivity of capital and of labor, z_k and z_n, and decreases in the interest, R, provided that $\varepsilon_m \neq 1$.

From (6) and (7), the optimal long-run effective capital per unit of effective labor is

$$\omega_i = \left[\left(\frac{z_k}{R} \right)^{1-\varepsilon_m} - 1 \right]^{\varepsilon_i/(1-\varepsilon_m)}. \tag{8}$$

Hence, ω_i increases with capital productivity, z_k; this effect is stronger if it is easier to substitute labor for capital (higher ε_i). Labor producitivty, z_n, on the other hand, does not affect relative effective use of inputs, ω_i, because the direct negative impact of z_n on ω_i and its indirect positive one on the wage cancel out exactly.[11]

Finally, imposing the fixed input proportions dictated by Equation (8), we obtain the short-run production function,

$$y_{it} = \left[1 + \omega_i^{(1-\varepsilon_i)/\varepsilon_i} \right]^{\varepsilon_i/(\varepsilon_i - 1)} z_k k_{it}. \tag{9}$$

Comparing with (1), we deduce that the productivity parameter Ω_i falls with ω_i for all $\varepsilon_i \neq 1$.

3.2 Short-run unemployment and long-run effects

We now use Equation (8) to obtain

$$\Omega_i = \left\{ 1 + \left[\left(\frac{z_k}{R} \right)^{1-\varepsilon_m} - 1 \right]^{(1-\varepsilon_i)/(1-\varepsilon_m)} \right\}^{\varepsilon_i/(\varepsilon_i - 1)}. \tag{10}$$

The ratio ω_i then defines Ω_i and the long-run outcome towards which the economy converges. In this long-run scenario, given that the total amount of available labor equals N, equilibrium on the labor market implies that

$$n^* = n_e^* + n_m^* = N. \tag{11}$$

[11]This is a consequence of the production function having constant returns to scale.

However, when a technology shock hits the economy, it does not move to the new long-run equilibrium immediately because of the presence of capital adjustment costs. Therefore, in the short-run, since capital and labor enter the production function in fixed proportions, 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 $k_i^* = z_n \omega_i n_i^* / z_k$. Notice that the long-run capital stocks are fully determined by the labor allocations under full employment.

More specifically, in the short run the firm decides how much to invest in gross capital formation taking input prices, the fixed capital-labor ratio associated to the specific technology in use, and the adjustment costs as given. From Equation (1), the firm solves the problem

$$\max_{x_{it}} \left\{ p_i \Omega_i \min\left\{ z_k k_{it}, \omega_i z_n n_{it} \right\} - R \sum_{j=1}^{t} (1-\delta)^{t-j} x_{ij} - w n_{it} \right\} \tag{12}$$

subject to the capital accumulation equation,

$$k_{it} = (1-\delta) k_{it-1} + x_{it}^{\phi}, \tag{13}$$

where x_{it} denotes investment capital, δ denotes the depreciation rate, k_{it-1} is the productive capital inherited from the previous period, and $\phi \in (0,1)$. The return R is defined as in the long-run problem. Notice that, however, in the long-run problem we 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.[12]

The first-order optimality conditions to this problem (for an interior solution) are

$$\begin{aligned} z_k k_{it} &= \omega_i z_n n_{it}, \\ x_{it} &= \left(p_i \Omega_i z_k \frac{\phi}{R} \right)^{\frac{1}{1-\phi}}. \end{aligned} \tag{14}$$

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 k_{it} can even decrease if ϕ is too low, because x_{it} vanishes as ϕ tends to zero. This is a consequence of diminishing returns to investment generated by the adjustment costs.

In the long-run, productive capital reaches the stock allowed by the total amount of labor available in the economy and the effect of an increase in z_k or z_n on total production, defined

[12] The terms affected by the sum operator in expression (12) 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.

as $y_{mt} + p_e y_{et}$, is positive. In the short-run, however, this is not necessarily the case.

To better understand this, consider an increase in z_k. At the optimum, Equation (1) implies that $y_{it} = \Omega_i z_k k_{it}$. Hence, a larger z_k has a positive direct effect on the output-capital ratio, $\Omega_i z_k$, but indirectly reduces Ω_i through its effect on the optimal amount of effective labor per unit of effective capital (i.e., ω_i, see Equation (8)). This latter impact is stronger if the elasticity between capital and labor ε_i is high, because then the increase in z_k can generate more involuntary unemployment.[13] So, in the short-run, if capital accumulation is sufficiently slow (i.e., ϕ sufficiently low) and the reduction of labor per unit of capital is sufficiently large (i.e, ε_i sufficiently high), the fall in the labor demand due to the larger ω_i can dominate the positive effect of a higher z_k, thus making output fall.[14]

Moving now to the effect of changes in z_n. It affects neither ω_i nor Ω_i. So, a higher z_n only serves to increase the long-run stock of capital (see the definition of ω_i in Equation (6)). Therefore, Equation (1) implies that a labor-augmenting productivity improvement will raise output both in the short-run and in the long-run as k_{it} converges toward the higher k_i^*, regardless of the elasticity of substitution.

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 elasticity of substitution between labor and capital is sufficiently high. This finding is a consequence of the following two testable predictions: a technology improvement in capital in a sector where it is easier to substitute labor for capital will lead to (1) a larger increase of output in the long-run, and (2) a smaller increase or even reduction of output in the short-run. A further testable prediction is that (3) a labor-augmenting improvement in productivity boosts output both in the short- and in the long-run.

[13] In Equation (6), z_k can generate short-run involuntary unemployment (i.e., a larger k_i^*/n_i^* when the increase of k_{it} is sufficiently small) if ε_i is sufficiently high. This also includes values of ε_i less than 1 because the wage w rises with z_k.

[14] The economic intuition behind this result is quite clear. Mathematically, however, we need some additional restrictions. More specifically, it is easy to show that dy_{it}/dz_k is negative if and only if

$$\left[\left(\frac{z_k}{R}\right)^{1-\varepsilon_m} - 1\right]^{(\varepsilon_m - \varepsilon_i)/(1-\varepsilon_m)} \left[(\varepsilon_i - 1)\left(\frac{z_k}{R}\right)^{1-\varepsilon_m} + 1\right] > 1.$$

Hence, in the non-extractive sector, because $\varepsilon_i = \varepsilon_m$, the derivative $dy_{it}/dz_k < 0$ if and only if $\varepsilon_i > 1$

Hypotheses testing Our strategy consists of two steps. First, we estimate the elasticities of substitution between labor and capital, and find that this elasticity is higher for the resource-rich than for the resource-poor sector. Second, given this insight, we use the above testable hypotheses to check whether the output of resource-rich sectors is more likely to experience larger increases in the long-run and declines in the short-run following a capital-augmenting increase in productivity.

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-sector differences in the elasticity of substitution between labor and capital. 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 elasticity of substitution between labor and capital is persistently higher in extractive industries.

For this, we first derive expressions from the model that allow recovering z_k, z_n, ε_e and ε_m, and then estimate them using cross-industry U.S. data (cf. Caselli and Coleman (2006)). We start from Equation (2) and allow R, w and ε_i to vary across time and sectors, and z_k and z_n to vary across time but not across sectors. Hence, Equations (2) and (6) become

$$y_{et} = \left[(z_{kt}k_{et})^{1-1/\varepsilon_{et}} + (z_{nt}n_{et})^{1-1/\varepsilon_{et}}\right]^{\frac{\varepsilon_{et}}{\varepsilon_{et}-1}}, \tag{15}$$

$$\frac{k_{et}}{n_{et}} = \left(\frac{z_{kt}}{z_{nt}}\right)^{\varepsilon_{et}-1}\left(\frac{w_{et}}{R_{et}}\right)^{\varepsilon_{et}}, \tag{16}$$

$$y_{mt} = \left[(z_{kt}k_{mt})^{1-1/\varepsilon_{mt}} + (z_{nt}n_{mt})^{1-1/\varepsilon_{mt}}\right]^{\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}}, \tag{17}$$

$$\frac{k_{mt}}{n_{mt}} = \left(\frac{z_{kt}}{z_{nt}}\right)^{\varepsilon_{mt}-1}\left(\frac{w_{mt}}{R_{mt}}\right)^{\varepsilon_{mt}}. \tag{18}$$

We can use these to obtain

$$z_{nt} = \frac{y_{it}}{n_{it}}\left(\frac{w_{it}n_{it}}{p_{it}y_{it}}\right)^{\frac{\varepsilon_{it}}{\varepsilon_{it}-1}}, \quad \text{for } i = e, m, \tag{19}$$

and

$$z_{kt} = \frac{y_{it}}{k_{it}}\left(\frac{R_{it}k_{it}}{p_{it}y_{it}}\right)^{\frac{\varepsilon_{it}}{\varepsilon_{it}-1}}, \quad \text{for } i = e, m. \tag{20}$$

[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.

Finally, equalizing Equations (19) and (20) across the two sectors delivers

$$\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}=\frac{\ln\left(\frac{y_{mt}/k_{mt}}{y_{et}/k_{et}}\right)-\frac{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}{\ln\left(\frac{w_{et}n_{et}}{p_{et}y_{et}}\right)}\ln\left(\frac{y_{mt}/n_{mt}}{y_{et}/n_{et}}\right)}{\frac{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}{\ln\left(\frac{w_{et}n_{et}}{p_{et}y_{et}}\right)}\ln\left(\frac{w_{mt}n_{mt}}{y_{mt}}\right)-\ln\left(\frac{R_{mt}k_{mt}}{p_{mt}y_{mt}}\right)} \tag{21}$$

and

$$\frac{\varepsilon_{et}}{\varepsilon_{et}-1}=\frac{\ln\left(\frac{y_{mt}/k_{mt}}{y_{et}/k_{et}}\right)+\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}\ln\left(\frac{R_{mt}k_{mt}}{p_{mt}y_{mt}}\right)}{\ln\left(\frac{R_{et}k_{et}}{p_{et}y_{et}}\right)}. \tag{22}$$

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 Equation (21). Then, taking ε_{mt} into Equation (22) gives ε_{et}. Finally, substituting ε_{mt} and ε_{et} into (19) and (20) gives z_{nt} and z_{kt}. We can thus obtain the elasticities of substitution between labor and capital for each of the two sectors and the common labor-augmenting and capital-augmenting productivities, at any given point in time.

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. 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}).[17]

The estimated time series for ε_{mt}, ε_{et}, z_{nt} and z_{kt} are depicted in Figures 1 and 2. Estimated elasticities are within the range estimated in the literature (e.g., Chirinko, 2008). We note that ε_{mt} is consistently below ε_{et} in Figure 1 throughout the examined period. This supports our hypothesis that the elasticity of substitution between capital and labor is persistently higher in the extractive activities.

3.5 Estimates of labor- and capital-augmenting productivity shocks

Figure 2 plots the estimated common 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 we employ these common productivity shocks in our core analysis in

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

[17]This is consistent, for example, with the computations undertaken by Caselli and Coleman (2006).

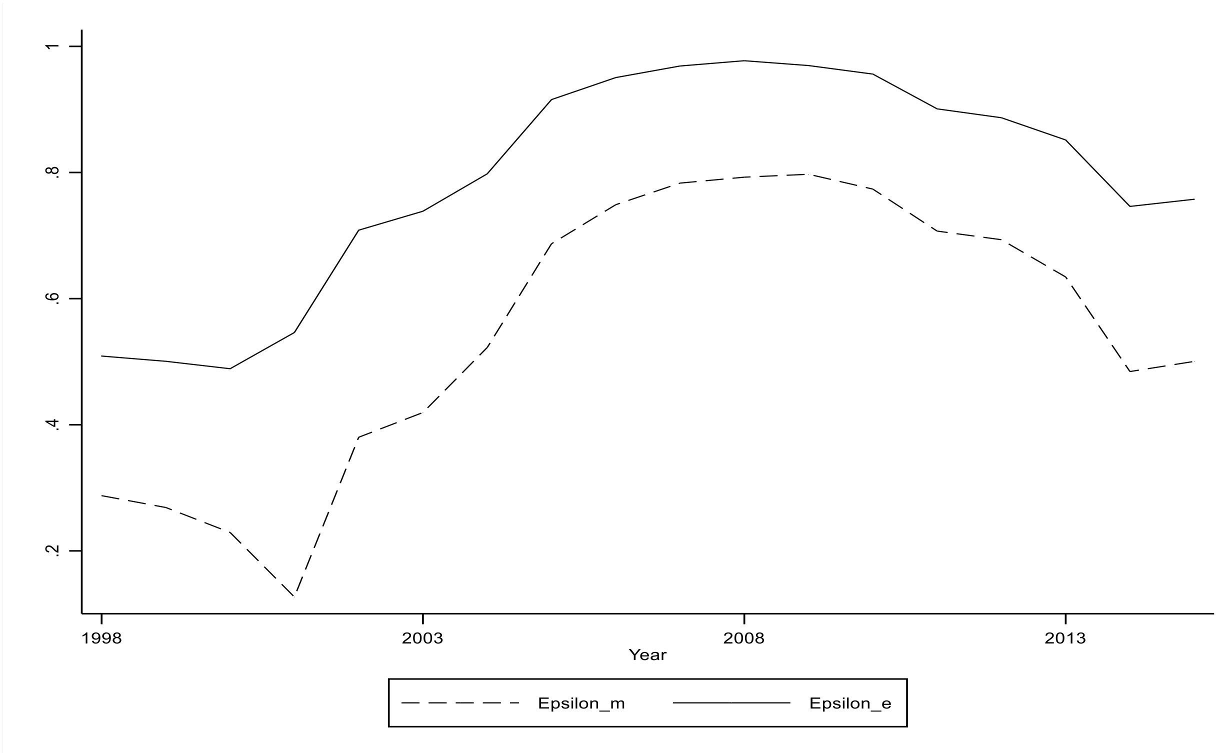

Figure 1: **Estimated elasticities of substitution between labor and capital are higher in mining and quarrying than in remaining sectors.** The estimates were computed from U.S. industry data retrieved from the EUKLEMS dataset (O'Mahony and Timmer, 2009) for the period 1998-2015. Industry e represents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

an attempt to examine their separate impact on growth in output and inputs, along the lines suggested by our analytical predictions.

3.6 Implications for resource-rich and resource-poor economies

To help understand the main implications of our analysis for resource-rich and resource-poor economies, we note that $\varepsilon_{et} > \varepsilon_{mt}$ as the empirical evidence presented in Figure 1 above suggests. Moreover, we note that resource-rich economies have a relatively large weight of the extractive sector e in gross domestic product, as illustrated empirically in the literature,[18] whereas in other economies the dominant industry are the remaining sectors m.

Our previous results thus imply that, in the case of resource-rich economies, aggregate output in the economy 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

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

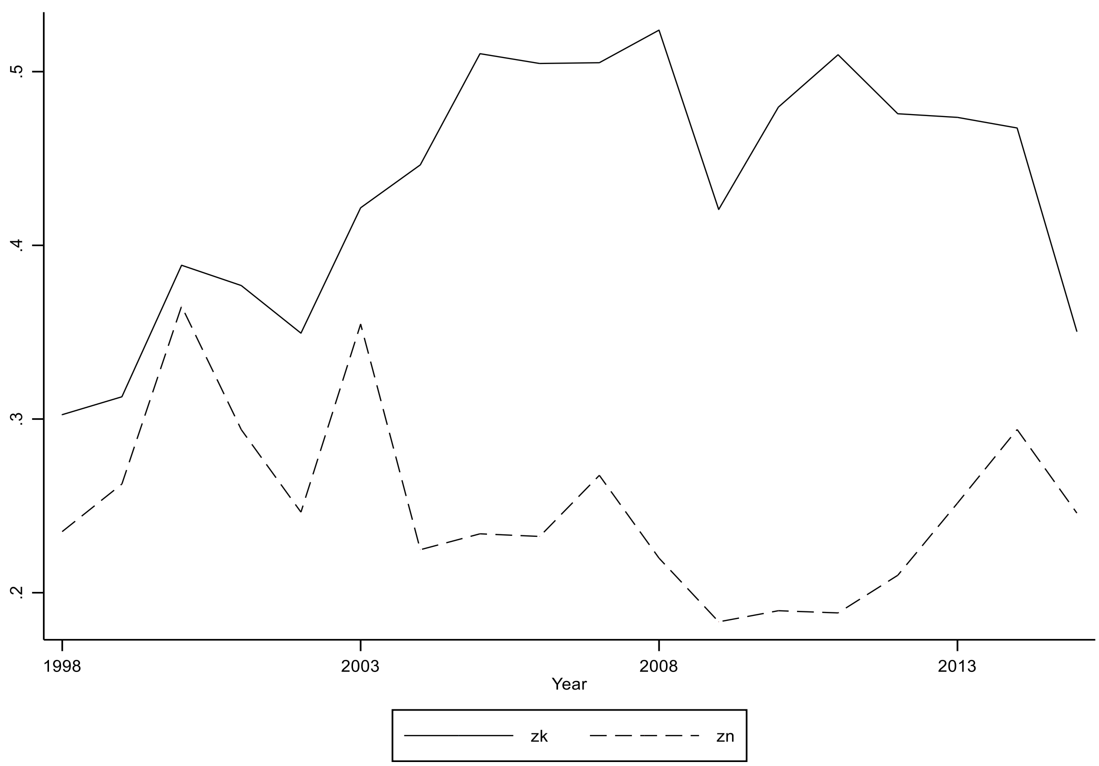

Figure 2: **Estimated common capital- and labor-augmenting productivity shocks.** Computed from U.S. industry data retrieved from the EUKLEMS dataset (O'Mahony and Timmer, 2009) for the period 1998-2015.

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 effect on income will be larger in resource-rich economies because the long-run rise in capital in these economies is larger than that in resource-poor ones.[19]

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 hetero-

[19]This results from differences in capital intensities, which in our analysis are determined by the assumed elasticity differences given their impact on the effective-input ratio ($\frac{z_k k_i}{z_n n_i}$). Empirical evidence for capital intensity differences across the natural resources dimension are discussed in Sections 1 and 2.

geneous 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.

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.[20] 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.[21] 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.[22] 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

[20] 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.

[21] 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.

[22] 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.

shocks to be exogenous for each state.[23] 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.

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 on the national TFP shocks, and their manifestation via resource intensity.[24] This data is derived from the U.S. Geological Survey at the province level, which James (2015) aggregates to the state level.[25] This provides the average endowment of natural resources per state, which we then normalize by state personal income, averaged over 1958-2008.

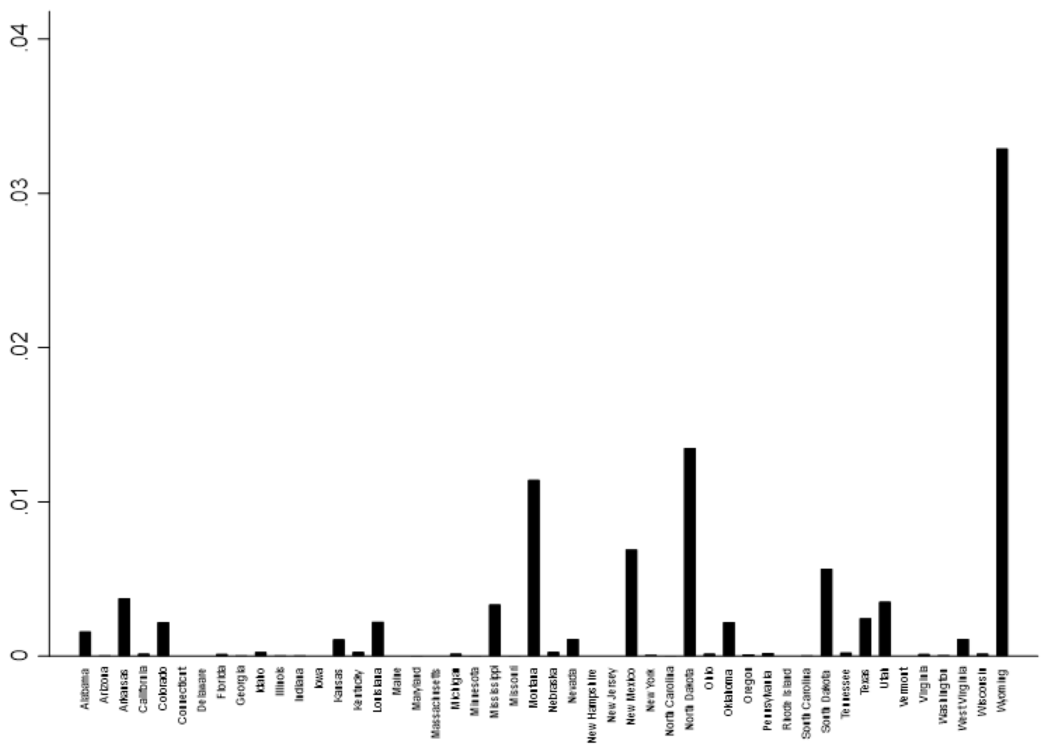

Figure 3: **Average resource endowment across the 48 continental U.S. states.** Source: James (2015).

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

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

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

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.[26] 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%.[27] Figure 3 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 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

$$\begin{aligned}\Delta(outcome)_{i,t} = \alpha + \beta(outcome)_{i,t-1} + \gamma(resource)_i \\ + \delta(tfp)_t + \theta(resource * tfp)_{i,t} + \eta_i + \nu_t + \epsilon_{i,t}\ , \quad (23)\end{aligned}$$

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.[28] These outcome variables represent the key macroeconomic indicators exam-

[26] 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 3).

[27] 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., James, 2015; Raveh, 2013).

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

ined by BFK, namely income and inputs.[29] 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 Section 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.[30]

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 addition, 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,

$$\Delta(unemp)_{i,t} = \alpha + \sum_{j=0}^{j=4} \beta(tfp)_{t-j} + \gamma(Year)_t + \eta_i + \epsilon_{i,t} \ , \tag{24}$$

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

[29] 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.

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

absorption of the state-invariant TFP shocks. Similar to BFK, contemporaneous TFP shocks are added together with four lags of TFP shocks.[31] 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.[32] 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.[33]

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 unemployment 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.[34] 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

[31] 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.

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

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

[34] 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.

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.

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.

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 Equation (23), for each of the three *outcome* variables. These core results are presented in Table 2.

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. 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.[35] The magnitude of this estimate of θ suggests, however, that the outcome is not only in relative terms. Furthermore, it points at a divergent outcome (cf. Table 1). This is also illustrated by Columns (2) and (3) of Table 2.

Table 2: **Resource endowments and effect of technology improvements, 1963-2015**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	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.

In Columns (2) and (3) of Table 2 we estimate a version of Equation (23) 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. Following 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.

[35]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.

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.

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 analysis in Section 3 indicates 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 zn and zk parameters computed and outlined previously in Section 4.1, 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 zk and zn 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 zk and zn, respectively. In each case, the first, second, and third column examine the *outcome* related to the output, labor, and capital measure, respectively.

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.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	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.

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 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.

Table 4 presents the robustness results when we allow for other sectors than natural resources. The other robustness results are presented in Table 5. 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. To examine how they might affect the impact of 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,[36] thus reaffirming the role of natural resources in understanding the effects of TFP shocks on state-level outcomes.

4.6.2 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 5, 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.

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

Table 4: **Results with other sectors than natural resources, 1963-2015**

Dependent variable: real per capita Gross State Product	(1) Manufacturing	(2) Services	(3) Agriculture	(4) Wholesale	(5) 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.

4.6.3 Results for three different alternative TFP measures

Columns (4)-(6) of Table 5 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.

4.6.4 Results with different sample restrictions, controls, and specifications

Columns (7)-(14) of Table 5 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, and test with a different clustering method. In Column (9), we include as controls government tax revenues per capita, government expenditure per capita, and population size. The latter provides a standard control for scale, and the former two account for the efficiency and size of the public sector, an important macroeconomic component besides inputs. In Column (10) 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 both cases indicate that our main result is robust to these additional controls.

In Columns (11)-(13) we re-estimate our model with three restricted samples. In Column (11) we exclude Montana, North Dakota, and Wyoming. Figure 3 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 (12) 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 (13) 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.

4.6.5 Results when resource measure is interacted with the oil price

As a final robustness test, 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 (14) 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.

4.7 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.

Table 5: **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)
	County analysis			TFP measures			Additional tests							
	TFP	Capital Augmenting	Labor Augmenting	Ford	BS	JPT	Pre-1997	Post-1996	Controls	Two-way clustering	Resource-rich excluded	No-resources excluded	Largest states excluded	Price
Resources X TFP	-0.13***						-0.15**	-2.37***	-0.4***	-0.48***	-1.46***	-0.47***	-0.47***	
	(0.03)						(0.71)	(0.2)	(0.08)	(0.17)	(0.3)	(0.07)	(0.08)	
Resources X Zk		-0.33***												
		(0.06)												
Resources X Zn			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)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.59	0.54	0.54	0.86	0.87	0.86	0.85	0.84	0.88	0.88	0.88	0.87	0.88	0.88
Observations	80594	31913	31913	2192	2096	2192	1576	904	2480	2480	2328	2272	2330	2480

Notes: Standard errors are robust, clustered by state (by county in Columns 1-3; by state and year in Column 10), 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 11 the sample excludes the three most resource-rich states: Montana, North Dakota, and Wyoming; in Column 12 the sample excludes states with zero resource endowments: Delaware, Maine, New Hampshire, and Rhode Island; in Column 13 the sample excludes the largest states: California, New York, and Texas) and covers the period: 1963-2015 in Columns 9-14, 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. '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)). '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)). '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, Primaceri, and Tambolotti (2011). 'Controls' include tax revenues per capita, population, and government expenditure per capita. For further information on variables see data Appendix.

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.[37] We employ the method of local-projections of Jorda (2005).

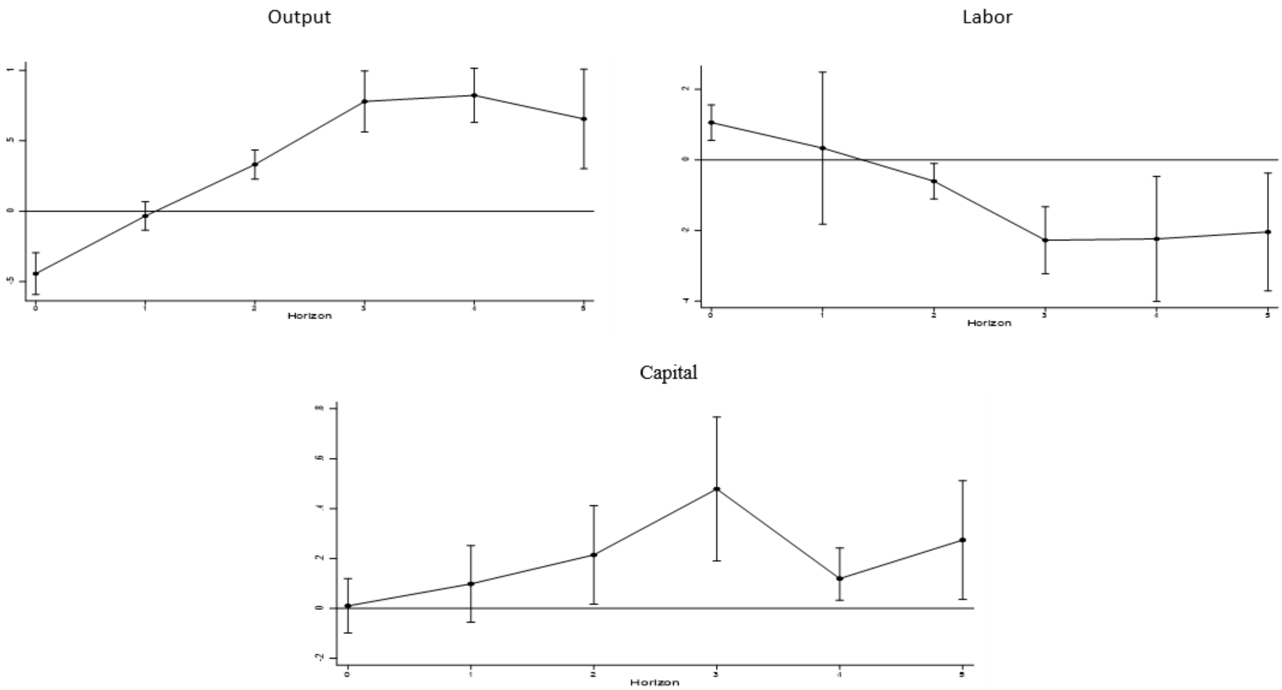

Figure 4: **Impulse response functions for the effect of TFP shocks.** The figure presents the impact of technology shocks interacted with resource endowments on the natural logarithms of real per capita GSP, the unemployment rate, and real per-capita investment over a 5-year horizon, with 95% confidence 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.

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.[38] We define $\Delta_{t-1}x_{i,t+h} \equiv x_{i,t+h} - x_{i,t-1}$ and estimate the sequential equations

$$\begin{aligned}\Delta_{t-1}(outcome)_{i,t+h} = \alpha^h + \beta^h(outcome)_{i,t-1} + \gamma^h(resource)_i \\ + \delta^h(tfp)_t + \theta^h(resource * tfp)_{i,t} + \eta_i^h + \nu_t^h + \epsilon_{i,t+h}. \quad (25)\end{aligned}$$

[37]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.

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

The dependent variable is the 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 4 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 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 elasticity between labor and capital 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, measures, 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.

Appendix

A 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.

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.

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).

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.

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
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
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.

B VAR analysis

In Section 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

$$\Delta(outcome)_{i,\Delta(t-1,t)} = \alpha + \beta(outcome)_{i,t-1} + \gamma(resource)_i + \delta(tfp)_t + \sum_{j=0}^{j=4} \theta_j (resource * tfp)_{i,t-j} + \eta_i + \nu_t + \epsilon_{i,t} \; . \quad (26)$$

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 Section 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 the 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.

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