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How Important Are Sectoral Shocks?[†]

By Enghin Atalay*

I quantify the contribution of sectoral shocks to business cycle fluctuations in aggregate output. I develop and estimate a multi-industry general equilibrium model in which each industry employs the material and capital goods produced by other sectors. Using data on US industries' input prices and input choices, I find that the goods produced by different industries are complements to one another as inputs in downstream industries' production functions. These complementarities indicate that industry-specific shocks are substantially more important than previously thought, accounting for at least half of aggregate volatility. (*JEL* D12, D24, E23, E32, L14)

What are the origins of business cycle fluctuations? Do idiosyncratic micro shocks—disturbances at individual firms or industries—have an important role in explaining short-run macroeconomic fluctuations? Or are shocks that prevail on all industries the predominant source?

I address these questions by constructing and estimating a multi-industry dynamic general equilibrium model in which both common and industry-specific shocks have the potential to contribute to aggregate output volatility. I find that sectoral shocks are important, accounting for considerably more than half of the variation in aggregate output growth.

A challenge in identifying the relative importance of industry-specific shocks is that, because of input-output linkages, both aggregate and industry-specific shocks have similar implications for data on industries' sales. To see why, consider the following two scenarios. In the first, some underlying event (e.g., a surprise increase in the federal funds rate) reduces the demand faced by all industries, including the auto parts manufacturing, steel manufacturing (a supplier of auto parts), and auto assembly industries. In the second scenario, a strike occurs in the auto parts manufacturing industry, which temporarily reduces the demand faced by sheet metal manufacturers, and increases the cost of establishments engaged in auto assembly. Even if industry-specific shocks are independent of one another, input-output linkages will

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induce co-movement in these industries' output and employment growth rates, just as in the first scenario. Intuitively, though, the more correlation across industry output growth that is observed, the more likely it is that common shocks are responsible for aggregate fluctuations.

But the extent to which industry activity co-moves depends on how easily consumers can substitute across the goods they consume, and how easily the firms within an industry can substitute across different factors of production. A particular amount of observed co-movement in output could result from one of two reasons. Production elasticities may be low, and common shocks relatively unimportant. Alternatively, elasticities of substitution may be large, and common shocks relatively important. The second challenge, then, emerges from the paucity of reliable, precise estimates of how easily industries can substitute across their inputs.[1]

In this paper, I confront these two related challenges sequentially. First, using data from the 1997 to 2013 BEA (Bureau of Economic Analysis) Annual Input-Output Tables, I estimate the relevant elasticities of substitution. In the data, the expenditure share of an industry on particular intermediate inputs are both volatile and positively correlated to the input's price. From these patterns, I estimate a relatively low value for the elasticity of substitution (which I call ε_M) among the intermediate inputs produced by different upstream industries: My point estimates of ε_M are consistently lower than 0.2, always significantly less than 1. In other words, different intermediate inputs are highly complementary to one another.

Second, armed with estimates of ε_M and the model's other salient elasticities of substitution, I construct a multi-industry dynamic general equilibrium model with which to infer industry productivity shocks. This model is an extension of that introduced in Foerster, Sarte, and Watson (2011), allowing for sectoral production functions that have non-unitary elasticities of substitution across inputs. Using the model, in conjunction with data on industries output levels from 1960–2013, I back out the productivity shocks that each industry experienced over this sample period. I then extract the common component of these productivity shocks.

From here, I compute the fraction of the variation in aggregate output growth that can be explained by industry-specific (versus common) shocks. I find that most of the variation in aggregate output growth is attributable to the industry-specific components, 83 percent in my benchmark estimates. When I impose unitary elasticities of substitution on my model, I estimate that 21 percent of the variation in output volatility comes from industry-specific shocks. In sum, these results indicate that sectoral shocks are more important than previously thought, and that the difference is largely due to past papers' imposition of a unitary elasticity of substitution across different inputs in sectoral production functions. These results are robust to countries, industry classification schemes, treatment of trends, and other modeling choices.

This paper resolves the hypothesis, first advanced in Long and Plosser (1983), that independent industry-specific shocks generate patterns characteristic of modern business cycles. Models of business cycles typically portray fluctuations as the

[1] I discuss existing estimates of the relevant elasticities in Section II.

result of economy-wide, aggregate disturbances to production technologies and preferences. These disturbances, however, are difficult to justify independently, and may simply represent “a measure of our ignorance.”[2] Given the results of the current paper, future research on the sources of business cycle fluctuations would benefit from moving beyond the predominant one-sector framework.

Related Literature.—The current paper falls within the literature on multi-industry real business cycle models initiated by Long and Plosser (1983). Long and Plosser present a model in which the economy is composed of a collection of perfectly competitive industries. Each industry produces its output by employing a combination of labor and intermediate inputs. The intermediate input bundles of each industry are, in turn, combinations of goods that are purchased from other industries. Long and Plosser (1983) and others in this literature (e.g., Horvath 1998 and 2000; Dupor 1999; Acemoglu et al. 2012; and Acemoglu, Ozdaglar, and Tahbaz-Salehi 2017) use this framework to argue that idiosyncratic shocks to industries’ productivities, by themselves, have the potential to generate substantial aggregate fluctuations.[3] These papers, however, do not allow for aggregate shocks.They are not attempting to assess the relative importance of industry-specific and aggregate shocks.

Uniquely among the aforementioned papers, the model in Horvath (2000) accommodates non-unitary elasticities of substitution in consumers’ preferences (across goods) and in the production of the intermediate input bundle (across inputs purchased from upstream industries).[4] His is the first article to articulate that lower elasticities of substitution “engender greater sectoral comovement… by reducing the ability of sectors to avoid the shocks of their input supplying sectors” (p. 83). A key difference between the current paper and Horvath (2000) is that the earlier paper does not attempt to estimate the values of these elasticities of substitution, nor does it seek to identify the role of common versus sectoral shocks in generating aggregate fluctuations.

So, compared to the Long and Plosser literature, the current paper makes three advances. First, I extend Foerster, Sarte, and Watson (2011)’s identification scheme to accommodate flexible substitution patterns in consumers’ preferences and industries’ production technologies. Second, using data on industries’ input usage and input prices, I estimate these production elasticities. Together, these two contributions are necessary to arrive at the paper’s main result, that industry-specific shocks play a much larger role in generating aggregate volatility than previously believed. As a tertiary contribution, I make a sequence of smaller advances. I allow

[2] This phrase was coined by Abramovitz (1956), when discussing the sources of long-run growth, but applies to our understanding of short-run aggregate fluctuations, as well. More recently, Summers (1986) and Cochrane (1994) have argued that it is a priori implausible that aggregate shocks can exist at the scale needed to engender the business cycle fluctuations that we observe.

[3] Among these papers, Dupor (1999) is exceptional. Instead of arguing that industry-specific shocks have the potential to produce business cycle fluctuations, he does the converse. He provides conditions on the input-output matrix under which industry-specific shocks are irrelevant.

[4] There are papers in other fields that focus more closely on these elasticities. Johnson (2014) and Boehm, Flaaen, and Pandalai-Nayar (2015a) study the transmission of shocks across international borders as a mechanism for generating cross-country co-movement and examine how the extent of model-predicted co-movement varies with production and preference elasticities.

for consumption good durability, consider a dataset that covers the entire economy,[5] and examine data from several developed economies.[6]

Outline.—In the remainder of the paper, I spell out the multi-sector real business cycle model (Section I); estimate how easily industries can substitute across inputs (Section II); apply these estimated elasticities to the real business cycle model to re-examine the relative importance of industry-specific shocks (Section III); and conclude (Section IV). In Appendix A, I provide some additional details on the datasets used in the paper.[7]

I. Model

In this section, I present a multi-industry general equilibrium model. This is the simplest model that can be used to compare the importance of industry-specific and aggregate disturbances, and to estimate the production elasticities of substitution. The model is populated by a representative consumer and N perfectly competitive industries. I first describe the representative consumer's preferences, then the production technology of each industry, and finally the evolution of the exogenous variables.

A. *Preferences*

The consumer has balanced growth-consistent preferences over leisure and the services provided by the N different consumption goods.[8]

The preferences of the consumer are given by the following utility function:

$$(1) \quad U = \sum_{t=0}^{\infty} \beta^t \left[\log \left[\left(\sum_{J=1}^{N} \xi_J^{\frac{1}{\varepsilon_D}} (C_{tJ})^{\frac{\varepsilon_D - 1}{\varepsilon_D}} \right)^{\frac{\varepsilon_D}{\varepsilon_D - 1}} \right] - \frac{\varepsilon_{LS}}{\varepsilon_{LS} + 1} \cdot \left(\sum_{J=1}^{N} L_{tJ} \right)^{\frac{\varepsilon_{LS}+1}{\varepsilon_{LS}}} \right].$$

The demand parameters, ξ_J, reflect the time-invariant differences in the importance of industries' goods in the consumer's preferences; C_{tJ} equals the final consumption purchases on good/service J at time t. The elasticities of substitution

[5] Foerster, Sarte, and Watson (2011) is unique in its application of the Federal Reserve Board's dataset on industrial production, a dataset that spans only the goods-producing sectors of the US economy. Other papers (e.g., Long and Plosser 1983, Horvath 2000, and Ando 2014), employ datasets that cover the entire economy.

[6] A parallel literature attempts to gauge the relative importance of industry-specific shocks by estimating vector autoregressions (see Long and Plosser 1987, Stockman 1988, Shea 2002, and Holly and Petrella 2012). Yet another line of research constructs simple summary statistics of shocks to the largest firms or industries, relates these summary statistics to aggregate output movements, and in this way establishes the importance of micro shocks. Gabaix (2011) defines the *granular residual*—changes in productivity to the largest 100 firms—and shows that this statistic explains approximately one-third of the variation in GDP (see also di Giovanni, Levchenko, and Mejean 2014). Along these lines, Carvalho and Gabaix (2013) show that a summary statistic, one which measures the relative sizes of industries with different productivity volatilities, can help explain time-varying aggregate volatility.

[7] In the online Appendices, I re-estimate one of the model's elasticities of substitution using plant-level data on manufacturers' input choices in online Appendix B, describe the datasets from other countries (online Appendix C), report on a sequence of robustness checks (online Appendices D and E), and characterize the solution of Section I's model (online Appendix F).

[8] In online Appendix F, I extend the model to accommodate durability of certain consumption goods. This turns out to increase moderately the estimated importance of sectoral shocks for certain parameter configurations, and has no noticeable effect for others; see online Appendix E.

parameterize how easily the representative consumer substitutes across the different consumption goods (ε_D) and how responsive the consumer's desired labor supply is to the prevailing wage (ε_{LS}).[9]

B. *Production and Market Clearing*

Each industry produces a quantity (Q_{tJ}) of good J at date t using capital (K_{tJ}), labor (L_{tJ}), and intermediate inputs (M_{tJ}) according to the following constant-returns-to-scale production function:

$$(2)\quad Q_{tJ} = A_{tJ} \cdot \left[(1-\mu_J)^{\frac{1}{\varepsilon_Q}} \left(\left(\frac{K_{tJ}}{\alpha_J}\right)^{\alpha_J} \left(\frac{L_{tJ}}{1-\alpha_J}\right)^{1-\alpha_J} \right)^{\frac{\varepsilon_Q - 1}{\varepsilon_Q}} + (\mu_J)^{\frac{1}{\varepsilon_Q}} (M_{tJ})^{\frac{\varepsilon_Q - 1}{\varepsilon_Q}} \right]^{\frac{\varepsilon_Q}{\varepsilon_Q - 1}}.$$

The parameters μ_J and α_J reflect long-run averages in each industry's usage of intermediate inputs, labor, and capital. These parameters will eventually be inferred from the factor cost shares of each industry. The variable A_{tJ} is the factor-neutral of industry J at time t. For now, these productivity terms can be correlated, across industries, in any arbitrary fashion. The parameter ε_Q dictates how easily factors of production are substituted.[10]

The evolution of capital, for each industry J, is given in equation (3):

$$(3)\quad K_{t+1,J} = (1-\delta_K) K_{tJ} + X_{tJ}.$$

The capital stock is augmented via an industry-specific investment good, X_{tJ}, and depreciates at a rate δ_K that is common across industries. The industry-specific investment good is produced by combining the goods produced by other industries. The Γ_{IJ}^X indicate how important industry I is in the production of the industry J specific investment good, while ε_X parameterizes the substitutability of different inputs in the production of each industry's investment bundle:

$$(4)\quad X_{tJ} = \left(\sum_{I=1}^{N} (\Gamma_{IJ}^X)^{\frac{1}{\varepsilon_X}} (X_{t,I\to J})^{\frac{\varepsilon_X - 1}{\varepsilon_X}} \right)^{\frac{\varepsilon_X}{\varepsilon_X - 1}}.$$

[9] Horvath (2000) and Kim and Kim (2006) use a more flexible specification regarding the disutility from supplying labor. In their specification, the second term in the period utility function is replaced by

$$-\frac{\varepsilon_{LS}}{\varepsilon_{LS}+1} \cdot \left(\sum_{J=1}^{N} (L_{tJ})^{\frac{\tau+1}{\tau}} \right)^{\frac{\tau}{\tau+1}\frac{\varepsilon_{LS}+1}{\varepsilon_{LS}}}.$$

The idea behind this specification is to "capture some degree of sector specificity to labor while not deviating from the representative consumer/worker assumption" (Horvath 2000, 76). As it turns out, neither the volatility of aggregate economic activity nor the covariances of output across industries are particularly sensitive to the value of τ (see Table 9 of that paper). Moreover, since wages and hours are not among the observable variables that I am trying to match, the data that I employ in the following sections would have trouble identifying τ. For these reasons, I use the simpler specification of the disutility from labor supply.

[10] In a robustness check (see column 2 of Table 4), I will consider labor-augmenting instead of TFP shocks. With ε_Q equal to 1, shocks to labor-augmenting productivity and TFP cannot be separately identified. With non-unitary elasticities of substitution, the paper's main results could a priori be sensitive to how the exogenous productivity term affects output.

Analogously, the intermediate input bundle of industry J is produced through a combination of the goods purchased from other industries:

$$M_{tJ} = \left(\sum_{I=1}^{N} \left(\Gamma_{IJ}^{M}\right)^{\frac{1}{\varepsilon_M}} \left(M_{t,I\to J}\right)^{\frac{\varepsilon_M - 1}{\varepsilon_M}} \right)^{\frac{\varepsilon_M}{\varepsilon_M - 1}}. \tag{5}$$

In equation (5), ε_M parameterizes the substitutability of different goods in the production of each industry's intermediate input bundle. The Γ_{IJ}^{M} indicate how important industry I is in the production of the industry J specific intermediate input.

To emphasize, the parameters Γ_{IJ}^{M}, Γ_{IJ}^{X}, α_J, and μ_J are time invariant. As such, movements in the share of J's expenditures spent on different factors of production are due, only, to the shocks to industries' productivity.

From the cost-minimization condition of the industry J representative firm, the relationship between the intermediate input cost share of industry J and the industry J specific intermediate input price (denoted P_{tJ}^{in}) is log-linear, with slope $1 - \varepsilon_Q$:[11]

$$\Delta \log\left(\frac{P_{tJ}^{in} \cdot M_{tJ}}{P_{tJ} \cdot Q_{tJ}}\right) = \left(1 - \varepsilon_Q\right) \cdot \Delta \log\left(\frac{P_{tJ}^{in}}{P_{tJ}}\right) + \left(\varepsilon_Q - 1\right) \cdot \Delta \log A_{tJ}. \tag{6}$$

A similar set of calculations yields the following relationship that describes changes in an industry's purchases of a specific intermediate input:

$$\Delta \log\left(\frac{P_{tI} M_{t,I\to J}}{P_{tJ}^{in} M_{tJ}}\right) = \left(1 - \varepsilon_M\right) \cdot \Delta \log\left(\frac{P_{tI}}{P_{tJ}^{in}}\right). \tag{7}$$

When $\varepsilon_Q = \varepsilon_M = 1$, as assumed in previous papers, an industry's input cost shares are constant, independent of input prices, a prediction that I will show to be at odds with the data.

Finally, the market-clearing condition for each industry states that output can be used for consumption, as an intermediate input, or to increase one of the N capital stocks:

$$Q_{tI} = C_{tI} + \sum_{J=1}^{N} \left(M_{t,I\to J} + X_{t,I\to J}\right). \tag{8}$$

[11] The equivalence between sales and costs in the denominator of the left-hand side of equation (6) comes from the assumption that each industry is perfectly competitive, with a constant returns-to-scale production function.

To derive equation (6), take first-order conditions of equation (2) with respect to intermediate input purchases:

$$\begin{aligned} P_{tJ}^{in} &= P_{tJ} \cdot \frac{\partial Q_{tJ}}{\partial M_{tJ}} \\ &= P_{tJ} \cdot \left(A_{tJ}\right)^{\frac{\varepsilon_Q - 1}{\varepsilon_Q}} \left(M_{tJ}\right)^{-\frac{1}{\varepsilon_Q}} \left(\mu_J \cdot Q_{tJ}\right)^{\frac{1}{\varepsilon_Q}}; \\ \left(P_{tJ}^{in}\right)^{\varepsilon_Q} &= \left(P_{tJ}\right)^{\varepsilon_Q} \left(A_{tJ}\right)^{\varepsilon_Q - 1} \left(M_{tJ}\right)^{-1} \mu_J \cdot Q_{tJ}. \end{aligned}$$

Taking logs, rearranging, and computing the difference across two adjacent periods gives equation (6).

C. *Evolution of the Exogenous Variables and the Model Filter*

Using A_t to denote the vector of productivity levels in the N industries, $(A_{t1}, \ldots, A_{tN})'$, I specify the evolution of productivity as a geometric random walk:

$$\log A_{t+1} = \log A_t + \omega_{t+1}^A. \tag{9}$$

For now, the productivity shocks' covariance matrices are left unspecified. I will add some structure to these matrices in Section III.

As in Foerster, Sarte, and Watson (2011), in a competitive equilibrium, the vector of industries' output growth rates admits a VARMA(1, 1) representation. Thus, the evolution of output can be written as

$$\Delta \log Q_{t+1} = \Pi_1 \Delta \log Q_t + \Pi_2 \omega_t^A + \Pi_3 \omega_{t+1}^A. \tag{10}$$

The $N \times N$ matrices Π_1, Π_2, and Π_3 are functions of the model parameters. I solve for these matrices in online Appendix F.

Solving equation (10) for ω_{t+1}^A yields the filter

$$\omega_{t+1}^A = (\Pi_3)^{-1} \Delta \log Q_{t+1} - (\Pi_3)^{-1} \Pi_1 \Delta \log Q_t - (\Pi_3)^{-1} \Pi_2 \omega_t^A. \tag{11}$$

With some initial condition for the productivity shock (e.g., $\omega_0^A = 0$), one could iteratively use data on sectoral growth rates to infer the productivity shocks at each point in time. I will apply this procedure in Section III. But first, I must determine values for the model's elasticities of substitution. The example in the following subsection explains why.

D. *Why Do the Elasticities Matter?*[12]

Before turning to the empirical analysis, I work through a special case of the model. This special case yields a relatively simple set of expressions for the relationship between the model parameters, the exogenous productivity shocks, and each industry's output. With this relationship in hand, I then discuss the intuition behind why imposing unitary elasticities of substitution may lead one to understate the role of industry-specific shocks.

Compared to the benchmark model, I make a number of simplifying assumptions. I assume that (i) all goods depreciate fully each period; (ii) there is no physical capital in production; (iii) each industry has identical production functions; (iv) the consumer's preference weight is the same for each of the N goods; and (v) the input-output matrix has $1/N$ in each entry. Relaxing these assumptions would not overturn the example's main message, that higher elasticities of substitution

[12] This subsection is related to the technical Appendix of Carvalho and Gabaix (2013). The main difference, besides assumptions (a)–(e), is that Carvalho and Gabaix impose that $\varepsilon_M = 1$ and allow for some adjustment costs to aggregate labor.

generate less correlated output for a given set of correlations among the underlying productivity shocks.

The overall aim of the paper's model is to use data on industries' output to recover the degree to which productivity shocks are correlated across industries. If industry output data indicate that productivity shocks are correlated, then aggregate shocks will be assigned to play a primary role in generating industries' output (and, correspondingly, aggregate output) fluctuations. With this in mind, in online Appendix F.6, I work out the following (log-linear, around the point at which $A_I = 1$ for all I) approximation for each industry's output as a function of the productivity in each industry:

$$(12) \quad \log Q_{tI} \approx \log \frac{1}{N} + \frac{1}{1-\mu} \log \left(\frac{1}{1-\mu} \right) + \underbrace{\left(\mu \varepsilon_M + (1-\mu) \varepsilon_D \right)}_{①} \log A_{tI} + \frac{1}{N} \underbrace{\left[\left(\frac{1}{1-\mu} \right)^2 - \left(\mu \varepsilon_M + (1-\mu) \varepsilon_D \right) \right]}_{②} \sum_{J=1}^{N} \log A_{tJ}.$$

Equation (12) is helpful as it allows one to relate the covariance of industries' gross output as a function of industries' productivity shocks, and thus describes how one could recover the correlation of productivity shocks from data on gross output. The terms ① and ② in equation (12) respectively specify the impact of industry-specific and common productivity changes on industry I's output level. Term ① is increasing in the two elasticities of substitution, ε_D and ε_M, and is minimized and equal to 0 when $\varepsilon_D = \varepsilon_M = 0$. In other words, regardless of the underlying correlation of the productivity terms, when production and preference elasticities are low, observed output will tend to strongly co-move. In contrast, in economies with larger production and preference elasticities, output will tend to co-move less for a given degree of correlation in the A terms.

In sum, the main takeaway from this simple example is that a given amount of observed output co-movement could arise either from low elasticities of substitution and correlated shocks or, alternatively, high elasticities of substitution and relatively uncorrelated shocks. So, to properly assess how important common versus independent shocks are, I must have reliable estimates parameterizing consumers' and firms' ease of substitution. This is the task to which I turn in the following section.

Before doing so, with the aim of providing the reader with some intuition, I briefly address a recurring question that I received while presenting this paper: Is the amplification of industry-specific shocks—where *amplification* is defined, here, as the aggregate output response following a shock in an individual sector—more severe with complementarities in production? On the one hand, when inputs are more complementary a (negative) productivity shock to a supplying industry (e.g., Steel) will lead to larger decreases in output for downstream industries (e.g., Motor Vehicles, Construction, etc…). On the other hand, the output decline in the industry experiencing the productivity shock will be smaller when its output is more complementary to the output of other industries. These two countervailing effects balance each other out in this simple example. Indeed, this must be the case, as the simple example of this subsection falls within the class of models studied in Hulten

(1978) and Acemoglu et al. (2012). For this class of models, the aggregate impact of shocks to an individual sector is only a function of the sector's gross output share; to a first-order, the elasticities of substitution do not matter. Instead, the elasticities matter because they alter the way in which co-movement in fundamental shocks map to co-movement in observable data.

II. Estimates of the Production Elasticities

In this section, I estimate the model's key elasticities of substitution. With this goal in mind, I will apply industries' cost-minimization conditions, as given in equations (6) and (7), to estimate ε_M and ε_Q. Recognizing the endogeneity of relative prices on the right-hand sides of these equations, I follow Shea (1993), Young (2014), and, especially, Acemoglu, Akcigit, and Kerr (2016) and use short-run industry-specific demand shifters as instruments. These shifts in demand arise from changes in military spending.

For this section, I use data from the BEA's GDP by Industry and Input-Output Accounts data spanning 1997 to 2013. The main variables that I construct from these tables are changes in (i) industry J's output price index, $\Delta \log P_{tJ}$; (ii) its intermediate input price index, $\Delta \log P_{tJ}^{in}$; (iii) its intermediate input cost share, $\Delta \log((P_{tJ}^{in} M_{tJ})/(P_{tJ} Q_{tJ}))$; and (iv) the fraction of industry J's intermediate input cost shares that are due to purchases from industry I, $\Delta \log((P_{tI} M_{t,I\to J})/(P_{tJ}^{in} M_{tJ}))$. So that I may combine production elasticity estimates with Dale Jorgenson's KLEMS data (which will be used in the following section), I collapse the 71 industries in the BEA data down to 30 industries. Appendix A contains a detailed description of the construction of the variables used in this section.

For 4 of the 30 industries, Figure 1 presents the relationship between $\Delta \log((P_{tI} M_{t,I\to J})/(P_{tJ}^{in} M_{tJ}))$ and $\Delta \log\left(P_{tI}/P_{tJ}^{in}\right)$ for J's most important supplier industry. As an example, for the furniture industry, which is depicted in panel B, I plot the furniture industry's intermediate input expenditure share of lumber on the y-axis, and the price of lumber relative to the price of furniture's intermediate input bundle on the x-axis. The numbers on the plot give the last two digits of the year t. The main takeaway is that the share of a particular input among total intermediate input expenditures is positively correlated to the price of that input (relative to other intermediate inputs); this relationship is statistically significant for three out of the four industries (nonmetallic minerals being the exception). Absent any omitted variables, equation (7) would yield an unbiased estimate of $1 - \varepsilon_M$: The slope of $\Delta \log ((P_{tI} M_{t,I\to J})/(P_{tJ}^{in} M_{tJ}))$ on $\Delta \log\left(P_{tI}/P_{tJ}^{in}\right)$, averaging across the four plotted industries, is 0.85, which would yield an estimate of $\varepsilon_M = 0.15$.[13]

Similarly, ε_Q, the elasticity of substitution between intermediate inputs and value added, could be identified off of the slope of the relationship between changes in the intermediate input cost share, $\Delta \log((P_{tJ}^{in} M_{tJ})/(P_{tJ} Q_{tJ}))$, and the relative price of intermediate inputs, $\Delta \log\left(P_{tJ}^{in}/P_{tJ}\right)$. Figure 2 plots this. All else equal, when ε_Q is less than 1, higher intermediate input prices are correlated with larger fractions

[13] These four industries are broadly representative of those throughout the sample. In online Appendix D, I depict this same relationship for all 30 industries.

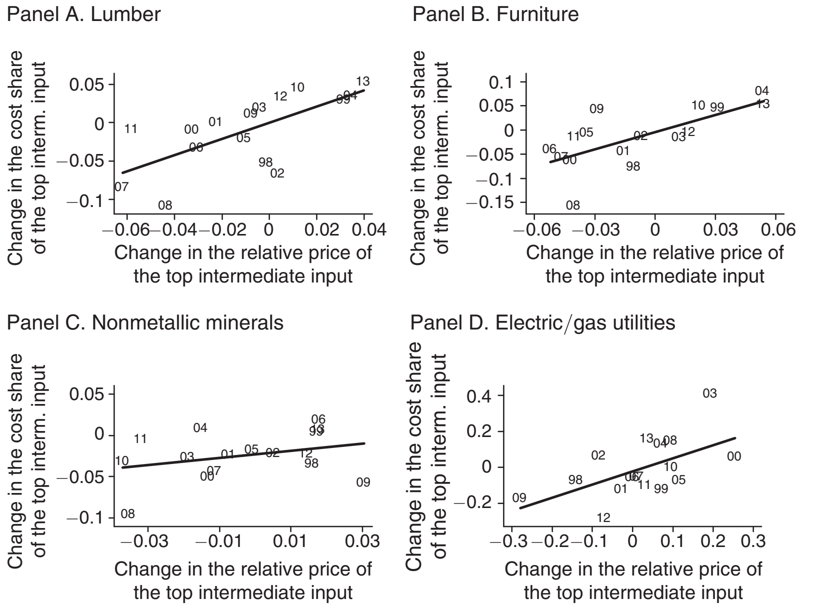

Figure 1. Relationship between Changes in Intermediate Input Purchases and Intermediate Input Prices

Notes: For each downstream industry, J, I take the most important (highest average intermediate input expenditure share) supplier industry, I. The x-axis of each panel gives $\Delta \log(P_{tI}/P_{tJ}^{in})$. The y-axis gives, for each industry, changes in the fraction of industry J's intermediate input expenditures that go to industry I.

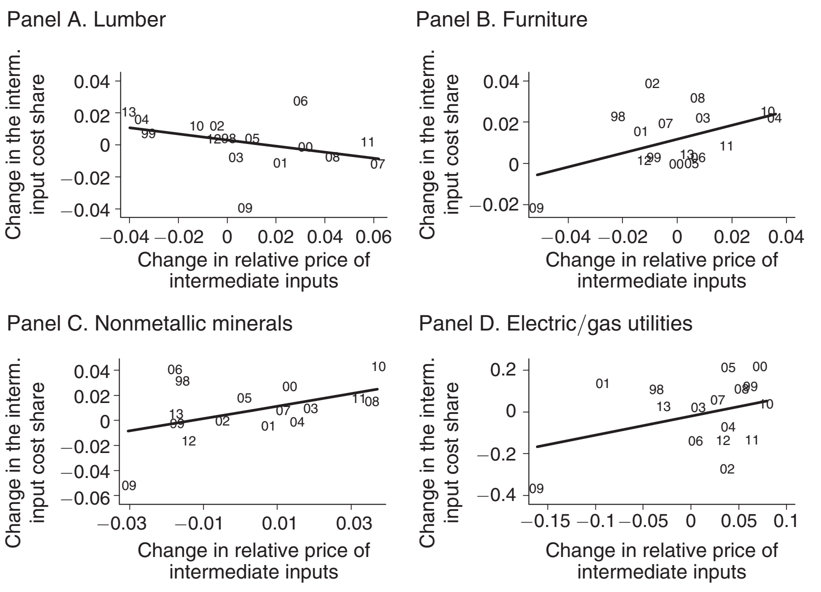

Figure 2. Relationship between Changes in Purchases of the Intermediate Input Bundle and the Relative Price of the Intermediate Input Bundle

Notes: For each industry, J, I plot the relationship between changes in its cost share of intermediate inputs on the y-axis, and changes in the difference between the price of the intermediate input bundle and the marginal cost of production on the x-axis.

of expenditures spent on intermediate inputs. For many, but certainly not all industries, this seems to be the case. The slope between $\Delta \log\left(\left(P_{tJ}^{in} M_{tJ}\right)/\left(P_{tJ} Q_{tJ}\right)\right)$ and $\Delta \log\left(P_{tJ}^{in}/P_{tJ}\right)$ is statistically distinct from 0 for 12 of the 30 industries: negative for 3 of the commodity-related industries—petroleum/gas extraction, petroleum refining, and primary metal manufacturing—and positive for 9 other industries. Overall, the slope of this line, for the average industry equals 0.4.

With the aim of more formally estimating ε_Q and ε_M, combine the cost-minimization conditions of each industry given in equations (6) and (7):

$$\text{(13)} \quad \Delta \log\left(\frac{P_{tI} M_{t,I\to J}}{P_{tJ} Q_{tJ}}\right) = \phi_t + \left(\varepsilon_M - 1\right)\left(\Delta \log P_{tJ}^{in} - \Delta \log P_{tI}\right) + \left(\varepsilon_Q - 1\right)\left(\Delta \log P_{tJ} - \Delta \log P_{tJ}^{in}\right) + \eta_{t,IJ}.$$

Shifts in relative productivity, which are correlated with changes in relative prices and enter the error term in equation (13), may lead to biased estimates of the production elasticities. According to the model presented in Section I, shocks to industries' final demand would alter industries' demand for specific factors only through their effects on relative prices. I use a set of instruments from Acemoglu, Akcigit, and Kerr (2016) to capture these shifts in final demand.[14]

I define a set of three instruments, which exploit annual variation in military spending and heterogeneity in the extent to which different industries are suppliers to, either directly or indirectly, the military. They are defined as

$$\text{(14)} \quad \text{military spending shock}_{tJ} \equiv \sum_{I'} \text{Output\%}_{1997,J\to I'} \times \mathcal{S}_{1997,I'\to\text{military}} \cdot \Delta \log(\text{Military Spending}_t),$$

$$\text{(15)} \quad \text{military spending shock}_{tI} \equiv \sum_{I'} \text{Output\%}_{1997,I\to I'} \times \mathcal{S}_{1997,I'\to\text{military}} \Delta \log(\text{Military Spending}_t),$$

and

$$\text{(16)} \quad \text{military spending shock}_{tJ\text{'s suppliers}} \equiv \sum_{I} \frac{P_{tI} M_{t,I\to J}}{P_{tJ}^{in} M_{tJ}} \text{military spending shock}_{tI}.$$

With these three separate instruments, I aim to capture demand shifts that lead, respectively, to changes in P_{tJ}, P_{tI}, and P_{tJ}^{in}, which are conditionally uncorrelated with $\eta_{t,IJ}$. In these equations, $\mathcal{S}_{1997,I\to\text{military}}$ is the share of industry I's output that

[14] The other demand shifter used by Acemoglu, Akcigit, and Kerr (2016) focuses on changes in industry demand resulting from China's consequential export expansion. Between 1995 and 2011, China's gross output exports to the United States, as a share of US GDP, has increased from 0.5 percent to 2.7 percent. More importantly for the purposes of the current paper, growth in China's exports to the United States dramatically differ across industries. But, in the first-stage estimates of equation (13), increased exports from China are associated with an *increase* in prices, counter to the motivation for the instrument.

is purchased by the "Federal National Defense" industries.[15] According to equation (14), demand for an industry J's output will vary due to fluctuations in military spending if it is a direct supplier to the military, if its main customers are important suppliers to the military, or if its main customers are indirect suppliers to the military. Among the industries in the sample, the "other transportation industry," in which ships, airplanes, and tanks are manufactured, has the highest $\mathcal{S}_{1997, I \to \text{military}}$. This industry has the strongest direct relationship with the military. Industries that are, on the other hand, indirectly reliant on purchases from the military include "instruments" and "petroleum refining." Equation (15) is identical to equation (14) except for the I subscript. And, to construct the military spending $\text{shock}_{tJ\text{'s suppliers}}$, I compute the average military spending shock of industries I, weighting each supplying industry by the extent to which they supplied intermediate inputs to industry J.

Table 1 presents the coefficient estimates from regressions defined by equation (13). The first two columns present OLS estimates. In the IV specifications, given in the final two columns, the instruments have the expected relationship with the relative price variables: Increased demand from federal spending is positively related with the price of that industry's good. In these specifications, the instruments are sufficiently powerful to yield reliable, unbiased estimates of ε_M and ε_Q. For these specifications, the point estimates are actually slightly negative ε_M, around -0.1, though one cannot reject 0 (or slightly positive values) for this elasticity of substitution. The right endpoint of a 90 percent confidence interval is approximately 0.2. For ε_Q, the OLS estimates result in an estimate of 1.2–1.3; the IV specifications produce estimates closer to 0.8–0.9. In these specifications, the standard errors for ε_Q are substantially larger: unit elasticities—as used previously in the literature—cannot be rejected.

In online Appendix D, I report results from regressions that estimate the slopes of the relationships between input expenditures and prices for different countries; using different—either coarser (with 9 industries) or finer (with 67 industries)—industry classification schemes; using a longer definition of a time period; and specifications for which these slopes are separately estimated for different subsamples of industries. The results in the Appendix accord with those presented in Table 1. Here, I summarize the results of these exercises. First, with more coarsely defined industries, the estimated elasticities are similar, but the instruments in the IV specifications are now weak. Second, estimates of ε_M and ε_Q are nearly identical to those in Table 1 with samples that include more upstream observations per downstream observation $\times$ year. Third, estimates of ε_M are somewhat larger, and estimates of ε_Q are somewhat smaller, with longer time periods (two years, instead of one year). Fourth, using the World Input Output Tables (WIOT), I estimate the slopes of intermediate input cost share versus intermediate input price relationships for a sample of six developed countries—Denmark, France, Italy, Japan, the Netherlands, and

[15] To define $\text{Output\%}_{1997, J \to I'}$, write $\mathcal{S}_{1997, J \to I'}$ as the share of industry J's output that is purchased by industry I' and store these elements in a matrix $\mathbf{S}$. Then, $\text{Output\%}_{1997, J \to I'}$ is the J, I' element of the matrix $\mathbf{I} + \mathbf{S} + \mathbf{S}^2 + \mathbf{S}^3 + \ldots = (\mathbf{I} - \mathbf{S})^{-1}$.

Note that while Acemoglu, Akcigit, and Kerr (2016) motivate this definition using Cobb-Douglas sectoral production functions, the same definition—as a demand shifter—is compatible with CES production functions as well. See online Appendix F.7.

Table 1—Regression Results Related to Equation (13)

Second-stage regression results	(1)	(2)	(3)	(4)
ε_M	−0.07	−0.13	−0.13	−0.11
	(0.04)	(0.04)	(0.19)	(0.20)
ε_Q	1.18	1.27	0.84	0.88
	(0.06)	(0.06)	(0.44)	(0.35)
First stage: dependent variable is $\Delta \log P_{tJ}^{in} - \log P_{tI}$				
military spending shock$_{tI}$			−0.75	−0.70
			(0.06)	(0.06)
military spending shock$_{tJ\text{'s suppliers}}$			0.96	1.11
			(0.09)	(0.12)
military spending shock$_{tJ}$			−0.12	−0.14
			(0.07)	(0.06)
F-statistic			66.42	17.48
First stage: dependent variable is $\Delta \log P_{tJ} - \log P_{tJ}^{in}$				
military spending shock$_{tI}$			−0.13	0.00
			(0.04)	(0.04)
military spending shock$_{tJ\text{'s suppliers}}$			−0.30	0.11
			(0.06)	(0.08)
military spending shock$_{tJ}$			0.38	0.35
			(0.04)	(0.04)
F-statistic			28.04	12.31
Cragg-Donald statistic			27.04[i]	40.54[i]
Wu-Hausman test *p*-value			0.66	0.52
Year fixed effects	No	Yes	No	Yes
Observations	4,800	4,800	4,592	4,592

Notes: The overall sample includes pairs of industries *J*, and, for each industry *J*, the top ten supplying industries, *I*. In the third and fourth columns, the sample size is reduced because of the exclusion of the government industry. In the row labeled "Cragg-Donald Statistic," an "i" indicates that the test for a weak instrument is rejected at the 10 percent threshold. Within this table, the "military spending shock$_{tJ}$" term, the "military spending shock$_{tI}$" term, and the "military spending shock$_{tJ\text{'s suppliers}}$" term are given by equations (14), (15), and (16). These three military shock terms are meant to predict changes in the three price terms that appear on the right-hand side of equation (13).

Spain. While, for these countries, I cannot apply variation in military spending as an instrument, the OLS estimates for these six countries are similar to those in the first two columns of Table 1: the estimates of ε_M are slightly larger (though still significantly smaller than 1), while estimates of ε_Q are somewhat smaller. In sum, the results from Table 1 are broadly, but not universally, robust to different samples and specifications. In all specifications, ε_M is safely well below 1.

While I am not aware of any previous research aimed at estimating ε_M, the estimates of ε_Q presented in Table 1 accord with the few existing estimates for this parameter.[16] Rotemberg and Woodford (1996) estimate ε_Q by running a regression

[16] Boehm, Flaaen, and Pandalai-Nayar (2015b) study the impact of the 2011 Tōhoku earthquake on the input purchases of US multinational firms that had a presence in Japan. Using exogenous variation provided by the earthquake, Boehm, Flaaen, and Pandalai-Nayar (2015b) estimate a firm-level elasticity of substitution between capital/labor and intermediate inputs (their ζ) and a firm-level elasticity of substitution between intermediate inputs sourced from Japan and everywhere else (their ω). The former elasticity corresponds to a firm-level version of this paper's

of manufacturing industries' intermediate input expenditure shares against the relative price of intermediate inputs, instrumenting the relative price of intermediate inputs using the price of crude oil. For industries within the manufacturing sector, Rotemberg and Woodford estimate a value of 0.7 for the elasticity of substitution between the capital-labor and the intermediate input bundles. More recent papers, using variation in the unit prices that individual plants pay for different factors, yield estimates of ε_Q in a similar range. Oberfield and Raval (2014) regress plants' intermediate input cost shares against the wages prevailing in their local labor markets, then combine this plant-level estimate with information on within-industry dispersion in plants' intermediate input intensities to build an industry-level estimate of ε_Q. Their estimates of ε_Q lie between 0.6 and 0.9. In online Appendix B, I follow a similar strategy, exploiting spatial variation in materials prices instead of spatial variation in wages. I arrive at estimates of ε_Q in the 0.4 to 0.8 range.

The model's other elasticities of substitution, in particular ε_D and ε_{LS}, will turn out to play only a secondary role in determining the importance of aggregate fluctuations. For these parameters, I will choose a wide range, centered around values that have been estimated in previous papers. With respect to the estimate of ε_D, Herrendorf, Rogerson, and Valentinyi (2013) consider long-run changes in broad sectors' relative prices and final consumption expenditure shares. Their benchmark estimate of the preference elasticity of substitution between expenditures on agricultural products, manufactured goods, and services is 0.9.[17,18] Regarding ε_{LS}, an extensive literature has estimated the Frisch labor supply elasticity, with estimates varying between 0.5 and 3; see Prescott (2006) and Chetty et al. (2011) for two syntheses of this literature.

To summarize, Table 1 suggests that a value for ε_M close to 0 and one for ε_Q that is close to but less than 1 faithfully describe industries' ability to substitute across inputs. In the following section, I will refer to $\varepsilon_M = 0.1$, $\varepsilon_Q = 1$, and $\varepsilon_D = 1$ as my benchmark set of parameter values.[19] However, since the standard errors of ε_Q are somewhat large, and since I have not even attempted to identify ε_X, ε_D, or ε_{LS}, it

ε_Q; see Oberfield and Raval (2014) or the current paper's online Appendix B for an explanation on how elasticities of substitution in firm-level and industry-level production functions can differ. The latter estimate is similar in spirit, but distinct from, a firm-level version of ε_M.

[17] With respect to an industry classification scheme closer to the one used in the current paper, Ngai and Pissarides (2007) argue that "the observed positive correlation between employment growth and relative price inflation across two-digit sectors" (p. 430) supports an estimate of ε_D that is less than 1. Also, Oberfield and Raval (2014) estimate a preference elasticity of between 0.8 and 1.1 across two-digit manufacturing industries.

[18] To emphasize, ε_D parameterizes how easily the consumer can substitute *across* coarsely defined industries' products (for example, the elasticity of substitution between Motor Vehicles and Furniture, or between Apparel and Construction). Broda and Weinstein (2006) and Foster, Haltiwanger, and Syverson (2008), among others, estimate a much larger elasticity of substitution in consumers' preferences. These larger elasticities of substitution are estimated using *within-industry* variation, and characterize how easily consumers substitute between, for example, ready-mix concrete produced by two different plants, or between different varieties of red wine.

[19] It is true that there is some weak evidence in favor of $\varepsilon_Q < 1$. However, given the large variability of the estimates of ε_Q, I will choose the conventional value of 1 for ε_Q for the benchmark parameter configuration, and consider a secondary specification with $\varepsilon_Q = 4/5$ in many of the other robustness checks.

The confidence intervals for ε_M in the final columns of Table 1 span both positive and negative values (in fact the point estimates from the IV regressions are negative). Negative, statistically distinguishable from zero estimates of ε_M would be troublesome, as this would indicate that some component of the Section I model is mis-specified. This is not the case here, but the choice of $\varepsilon_M = 0.1$ does require some justification. I choose 0.1 as my benchmark value for ε_M as it lies in the middle of positive portion of the 90 percent confidence interval for this parameter.

will be necessary to apply a range of values for these parameters. In the following section, I will compute the aggregate importance of sectoral shocks applying different reasonable combinations of ε_X, ε_Q, ε_M, and ε_D to Section I's model, and compare this estimated contribution of sectoral shocks to a calibration in which ε_X, ε_Q, ε_M, and ε_D are all set equal to 1.

III. Estimates of the Importance of Sectoral Shocks

This section contains the main results of the paper. In this section, I describe the calibration of certain parameters and the procedure with which I estimate the importance of common productivity shocks (Section IIIA); present the estimates of the importance of sectoral shocks for different values of the preference and production elasticities (Section IIIB); and examine the sensitivity of the benchmark results to changes in sample, industry definition, country, and other details of the estimation procedure (Section IIIC). I discuss additional robustness checks in online Appendix E.

A. *Calibration and Estimation Details*

Besides the preference and production elasticities, the model filter requires data on industries' output at each point in time along with information on the long-run average relationships across sectors. I discuss these two requirements in turn.

Regarding the data on industries' output, I combine Dale Jorgenson's 35-Sector KLEMS dataset (which spans the 1960 to 2005 period) with the output data from the BEA Industry Accounts (spanning 1997 to 2013) that were used in the previous section.[20] From these two datasets, I take information on industries' gross output, using industry-specific price deflators.

The parameters ξ_J, μ_J, α_J, Γ_{IJ}^X, and Γ_{IJ}^M are chosen to match the model-predicted cost shares to the corresponding values in the data. These parameters contain only information about the steady-state of the equilibrium allocation. The demand shares, ξ_J, are chosen so that the model's steady-state consumption choices are proportional to the amount that the industry sells to consumers or as government consumption expenditures; the ξ_J are restricted to sum to 1. The other parameters are chosen to match factor intensities, for each industry-factor pair. For instance, μ_J is the value that equates the model-predicted intermediate input cost share with the empirical counterpart.[21] The empirical values that are used to calibrate the factor intensities are described in Appendix A. Online Appendix F.1 provides additional details on the calibration of the parameters relevant to the steady state.[22]

[20] The Jorgenson data can be found at http://scholar.harvard.edu/jorgenson/data. Jorgenson, Gollop, and Fraumeni (1987) provide an extensive description of this dataset.

[21] When $\varepsilon_Q = 1$, the intermediate input cost share and μ_J are equal to one another. Alternatively, when intermediate inputs are gross complements or gross substitutes to other factors of production, the model-predicted cost share will also depend on the relative prices of the intermediate input bundle and the price of the other factors of production.

[22] In online Appendix E, I examine the sensitivity of Section IIIB's results to using 1972, instead of 1997, as the year to which the steady-state allocation is calibrated.

I choose β and δ_K based on the values used in past analyses. I set the discount factor, β, to 0.96 and the capital depreciation rate, δ_K, to 0.10. I set the labor supply elasticity, ε_{LS}, equal to 2, and explore the sensitivity of the main results to this parameter in Table 5.

These calibrated parameters define the Π_1, Π_2, and Π_3 matrices that appear in equation (11). This equation, which I reproduce for the reader's convenience below, can be used to infer each period's productivity shocks:

$$\omega_{t+1}^{A} = \left(\Pi_3\right)^{-1} \Delta \log Q_{t+1} - \left(\Pi_3\right)^{-1} \Pi_1 \Delta \log Q_t - \left(\Pi_3\right)^{-1} \Pi_2 \omega_t^{A}.$$

I apply two procedures to recover estimates of the ω^As. First, following the approach of Foerster, Sarte, and Watson (2011), I initialize the first-period productivity shocks at 0, $\omega_0 = 0$, and then iteratively apply equation (11). This procedure is infeasible for certain sets of parameter values. For particular parameter configurations, some eigenvalues of $\left(\Pi_3\right)^{-1}\Pi_2$ are greater than 1 in absolute value. In this case, data on output changes alone cannot fully identify the productivity shocks.[23] A second issue arises, as some of the eigenvalues of Π_3 continuously pass from positive to negative values (or vice versa) as the chosen calibrated parameters are continuously modified.[24] As a result, the smallest eigenvalue of Π_3 is close to zero for certain combinations of the calibrated parameters. When either of these two issues arise, as a second approach, I treat the initial productivity shocks as an unknown state, and apply the Kalman filter, using the output data in each period to iteratively produce estimates of each date's productivity innovation. In the parameter configurations for which the largest eigenvalue of $\left(\Pi_3\right)^{-1}\Pi_2$ is less than 1, and the smallest eigenvalue of Π_3 is sufficiently large, the two approaches produce the same estimates of the productivity shocks.

B. *Results*

With the estimates of ω in hand, I present two measures of the importance of sectoral shocks in shaping aggregate volatility. To compute the first measure, I perform factor analysis to extract the (single) common component of the ω^As. Then, with the covariance matrices of the industry-specific and common productivity shocks in hand, I recover the model-implied covariance matrices for industries' value added that result only from sector-specific shocks (call this Σ^{ind}) or from both sector-specific and common shocks (call this Σ^{all}).[25] With $\bar{v}$ denoting the N-dimensional vector that contains each industry's value added share, the fraction

[23] For parameter combinations for which at least one eigenvalue of $\left(\Pi_3\right)^{-1}\Pi_2$ is greater than 1 in absolute value, the "poor man's invertibility condition" in Fernández-Villaverde et al. (2007) is violated.

[24] To give an example, when ε_D, ε_M, and ε_Q equal 0.15, 0.25, and 1, and applying all of the other choices described in this subsection, the smallest eigenvalue of Π_3 is 0.036. Then, decreasing ε_M from 0.25 to 0.2 yields a minimum eigenvalue of Π_3 equal to -0.006. For ε_M near 0.2, then, the model filter given by equation (11) will yield unreliable estimates of the ω_t^A.

[25] Online Appendix F.5 explains the calculations behind Σ^{ind} and Σ^{all}.

of aggregate output volatility that is explained by the independent component of industries' productivity shocks is given by

$$(17) \qquad R^2(\text{sectoral shocks}) = \frac{\bar{v}'\Sigma^{\text{ind}}\bar{v}}{\bar{v}'\Sigma^{\text{all}}\bar{v}}.$$

The second measure of the relative importance of the common shocks is the average sample correlation of the productivity shocks:

$$(18) \qquad \bar{\rho}(\omega) = \sum_{I=1}^{N}\sum_{J=1}^{N} \text{corr}(\omega_i, \omega_j).$$

These two measures were also used by Foerster, Sarte, and Watson (2011) to summarize the importance of sectoral shocks.

Figure 3 displays these two summary measures for different values of ε_M and ε_Q. According to the left panel of this figure, when ε_D, ε_M, and ε_Q are all equal to 1—as is the case in almost all previous analyses of multi-sector real business cycle models—sector-specific shocks account for 21 percent of aggregate volatility.[26] For these same values of ε_D, ε_M, and ε_Q, the average correlation of the productivity shocks is 0.19.

A lower calibrated value for the elasticity of substitution among intermediate inputs yields estimates for industries' productivity shocks that are less correlated with one another. This relationship, which was the main takeaway of the simple example given in Section ID, is depicted in panel A of Figure 3. With ε_M and ε_D as 0.1 and 1, respectively, the filter results in productivity shocks that have an average correlation of 0.06. Put differently, the correlations among industries' output growth rates could arise either through productivity shocks that are relatively correlated and goods that have relatively high levels of substitutability, or through nearly independent productivity shocks and complementarity across the goods that industries produce.

With lower estimates of the correlation among productivity shocks, the common component of these shocks will account for a smaller fraction of aggregate volatility.

[26] Foerster, Sarte, and Watson (2011) also perform a factor analysis on industries' productivity shocks. They compute the fraction of industrial production growth that is due to the first two factors. The remaining variation can be considered equivalent to the industry-specific productivity shocks in the current paper. The two common factors explain 80 percent of the variation in overall industrial production growth in the first third of the sample (1972 to 1983) and 50 percent in the latter two-thirds (1984 to 2007). Averaging over these periods, sectoral shocks contribute roughly 40 percent of industrial production volatility.

There are a few potential explanations for why my figures may differ from those in Foerster, Sarte, and Watson (2011). One important difference is that the Foerster, Sarte, and Watson (2011) analysis is restricted to the goods-producing sectors of the economy, while I study the entire private economy; Ando (2014) explores the implications of this difference in coverage on the estimated contribution of industry-specific shocks. Other differences include a difference in sample period (1960 to 2013 in the current paper, compared to 1972 to 2008 in Foerster, Sarte, and Watson 2011), and period length (one quarter in Foerster, Sarte, and Watson 2011 versus one year, here). I show in the online Appendix that excluding the Great Recession somewhat increases the assessed role of industry-specific shocks: when $\varepsilon_D = \varepsilon_M = \varepsilon_Q = 1$, $R^2(\text{sectoral shocks})$ is 32 percent without the Great Recession, instead of 21 percent when the whole sample period is included. Decreasing the period length would, on the other hand, with $\varepsilon_M = 1$ and $\varepsilon_D = 1$, have little effect on the relative importance of sectoral shocks; see the fourth and fifth columns of online Appendix Table 15.

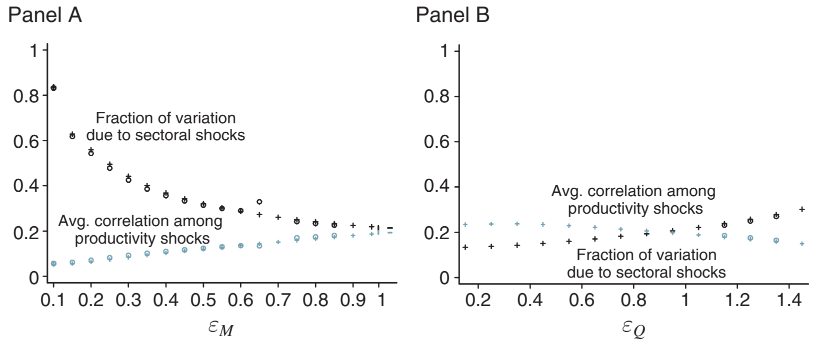

FIGURE 3. R^2(*sectoral shocks*) AND $\bar{\rho}(\omega)$ FOR DIFFERENT VALUES OF ε_M AND ε_Q

Notes: In panel A, $\varepsilon_Q = 1$. In panel B, $\varepsilon_M = 1$. In both panels, $\varepsilon_D = 1$. Hollow circles denote figures that result from the model filter, with ω_0 fixed at 0, iteratively applying equation (11). "+" signs denote the figures that result from the Kalman filter.

TABLE 2—ROBUSTNESS CHECKS: R^2(*sectoral shocks*) AND $\bar{\rho}(\omega)$ FOR DIFFERENT VALUES OF ε_D, ε_M, AND ε_Q

$\varepsilon_M, \varepsilon_D, \varepsilon_Q$	R^2(sectoral shocks)	$\bar{\rho}(\omega)$
$1, 1, 1$	0.21^{kf}	0.19^{kf}
$1, 1, \frac{4}{5}$	0.19^{kf}	0.21^{kf}
$\frac{1}{10}, \frac{3}{5}, 1$	0.98^{kf}	0.04^{kf}
$\frac{1}{10}, \frac{4}{5}, 1$	0.99^{kf}	0.04^{kf}
$\frac{1}{10}, 1, 1$	0.83	0.06
$\frac{1}{10}, \frac{6}{5}, 1$	0.63	0.07
$\frac{1}{10}, \frac{7}{5}, 1$	0.56	0.08
$\frac{1}{10}, \frac{8}{5}, 1$	0.49	0.10
$\frac{1}{10}, \frac{9}{5}, 1$	0.43	0.11

Note: A "kf" indicates the usage of the Kalman filter, as opposed to direct applications of equation (11) to infer the ω productivity shocks.

Indeed, for $\varepsilon_D = 1$ and $\varepsilon_Q = 1$, more than half of aggregate volatility is due to industry-specific shocks so long as $\varepsilon_M \leq 0.2$; see panel A of Figure 3. With our benchmark configuration—$(\varepsilon_D, \varepsilon_M, \varepsilon_Q)$ equal to $(1, 0.1, 1)$—83 percent of the variation of aggregate output is due to sectoral shocks. The right panel of this figure illustrates that R^2(sectoral shocks) is relatively unresponsive to the chosen value of ε_Q. This, too, accords with the example in Section ID. With $\varepsilon_M = 1$ and $\varepsilon_D = 1$, the fraction of variation explained by industry-specific TFP shocks is between 13 and 30 percent for $\varepsilon_Q \in [0.15, 1.45]$. In sum, within the range of elasticities that I have estimated in Section II, complementarities among intermediate inputs are important for assessing the role of aggregate fluctuations, but the elasticity of substitution between value added and intermediate inputs is not.

Table 2 expands on these results. In this table, I compute the fraction of variation explained by sectoral shocks for different ε_D, ε_M, and ε_Q combinations. As in Figure 3, fixing a unit elasticity of substitution across intermediate inputs results in

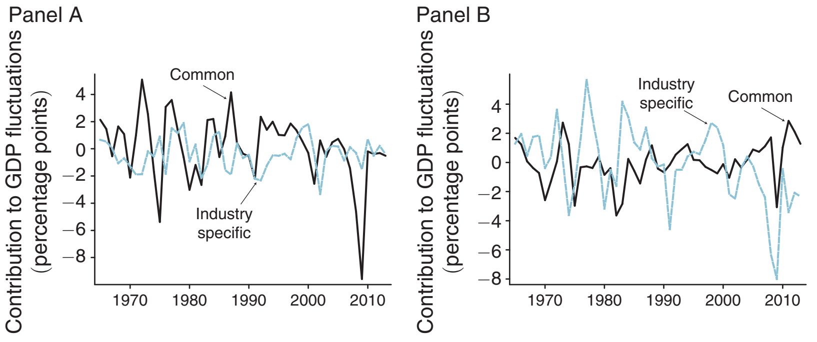

Figure 4. Historical Decompositions

Notes: The figure presents the percentage point change in each year's aggregate output (relative to trend) due to industry-specific and common shocks. In panel A, ε_D, ε_M, and ε_Q are all equal to 1. In panel B, $\varepsilon_M = 0.1$, $\varepsilon_D = 1$, and $\varepsilon_Q = 1$.

relatively high correlations among filtered productivity shocks, and a low estimated importance for industry-specific shocks. Even with improbably high values for ε_D, industry-specific shocks account for at least two-fifths of aggregate output volatility using Section II's estimate of ε_M.

Next, I examine whether the choice of elasticities has implications for individual historical episodes. Figure 4 presents historical decompositions for two choices of ε_M. In both panels, $\varepsilon_D = \varepsilon_Q = 1$. In panel A, I set $\varepsilon_M = 1$; and, in panel B, $\varepsilon_M = 0.1$. With relatively high elasticities of substitution across inputs, each and every recession between 1960 and the present day is explained almost exclusively by the common shocks. The sole partial exception is the relatively mild 2001 recession. In 2001 and 2002, Non-Electrical Machinery, Instruments, F.I.R.E. (Finance, Insurance, and Real Estate), and Electric/Gas Utilities—together accounting for GDP growth rates that were 2.0 percentage points below trend.

Table 3, along with panel B of Figure 4, presents historical decompositions, now allowing for complementarities across intermediate inputs. Here, industry-specific shocks are a primary driver, accounting for a larger fraction of most, but certainly not all of, recent recessions and booms. According to the model-inferred productivity shocks, the 1974–1975 and, especially, the early 1980s recessions were driven to a large extent by common shocks.[27] At the same time, the late 1990s expansion and the 2008–2009 recession are each more closely linked with industry-specific events. Instruments (essentially computer and electronic products) and F.I.R.E. had an outsize role in the 1996–2000 expansion, while wholesale/retail, construction, motor vehicles, and F.I.R.E. appear to have had a large role in the most recent recession. (Other services, due to its large gross output share, appears as an important industry

[27] While the common factor played a large role in the 1980s recessions, so too did the motor vehicles industry, especially in the first of the contractions. According to the model's historical decomposition, motor vehicles accounted for a 0.8 percent drop in aggregate output in 1979 and 1980.

Table 3—Historical Decompositions Using $\varepsilon_D = 1$, $\varepsilon_M = 0.1$, and $\varepsilon_Q = 1$

1974–1975		1980–1982	
Other services	−1.2	Other services	−1.4
Construction	−1.0	Construction	−0.7
Government	0.4	Motor vehicles	−0.5
Motor vehicles	−0.3	Warehousing	−0.4
Warehousing	−0.3	Wholesale and retail	−0.3
Common factor	−1.7	Common factor	−4.9
Total change	−6.9	Total change	−10.2
1996–2000		**2008–2009**	
Other services	1.7	Other services	−2.1
Instruments	0.9	Wholesale and retail	−1.8
F.I.R.E.	0.9	F.I.R.E.	−1.1
Construction	0.8	Construction	−1.0
Wholesale and retail	0.4	Motor vehicles	−0.6
Common factor	−1.6	Common factor	−1.4
Total change	6.8	Total change	−15.7

Notes: For four points in the sample, I report the five industries with the largest contributions to changes in aggregate output, the contribution of the common productivity shock, and the aggregate change in GDP, relative to trend. The stated changes are in percentage points.

in most periods.) These model-inferred productivity shocks align with contemporaneous historical accounts.[28]

C. *Sensitivity Analysis*

In Table 4, I examine the sensitivity of the assessed role of industry-specific shocks to the specification of productivity shocks, the industry classification scheme, and the calibration of industries' cost shares. In online Appendix F, I specify and characterize a model with labor-augmenting productivity shocks. The first column reiterates the benchmark estimates with TFP shocks. The second column applies labor-augmenting productivity shocks. With $\varepsilon_Q < 1$, sectoral shocks contribute a larger fraction to aggregate volatility when productivity is assumed to be labor augmenting. In the third column, I establish that the results of Figure 3 are qualitatively robust to an nine-industry partition of the economy.[29] In the fourth column, I use

[28] Related to the early 1980s recession, Friedlaender, Winston, and Wang (1983, 1–2) characterize the auto industry as "a state in flux. Not only has the Chrysler Corporation been perilously close to bankruptcy, but Ford and General Motors have suffered unprecedented losses in recent years." Regarding the 1996–2000 expansion, Jorgenson and Stiroh (2000) analyze the role of information-technology-producing and consuming industries as a source of productivity acceleration during this period. And, finally, regarding the latest recession, Goolsbee and Krueger (2015) and Boldrin et al. (2016), respectively, chronicle distresses in motor vehicles and construction.

[29] These industries are primary inputs (industries 1 to 3, according to Table A1), construction (industry 4), nondurable goods (industries 5 to 7 and 10 to 14), durable goods (industries 8, 9, and 15 to 23), transport and communications (industries 24 to 26), wholesale and retail (industry 27), F.I.R.E. (industry 28), personal and business services (industry 29), and government (industry 30). While it would be interesting to test the sensitivity of these results to a finer industry classification scheme, the necessary data are unavailable.

Table 4—Robustness Checks: R^2(*sectoral shocks*) and $\bar{\rho}(\omega)$ for Different Values of ε_D, ε_M, and ε_Q

	Benchmark	Labor-Aug. productivity	9-Industry classification	1972 IO table	Gov. dem. shocks
R^2(sectoral shocks)					
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (1, 1, 1)$	0.21^{kf}	0.21^{kf}	0.26	0.18^{kf}	0.22^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (1, 1, \frac{4}{5})$	0.19^{kf}	0.22^{kf}	0.23	0.16^{kf}	0.20^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, 1, \frac{4}{5})$	0.81	0.93	0.85^{kf}	0.98	0.81
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, \frac{2}{3}, 1)$	0.99^{kf}	0.99^{kf}	0.95	0.98^{kf}	0.99^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, 1, 1)$	0.83	0.83	0.82	1.00	0.83
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, \frac{4}{3}, 1)$	0.59	0.59	0.58	1.00	0.58
$\bar{\rho}(\omega)$					
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (1, 1, 1)$	0.19^{kf}	0.19^{kf}	0.26	0.17^{kf}	0.19^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (1, 1, \frac{4}{5})$	0.21^{kf}	0.19^{kf}	0.29	0.19^{kf}	0.21^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, 1, \frac{4}{5})$	0.06	0.07	0.15^{kf}	0.05	0.06
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, \frac{2}{3}, 1)$	0.04^{kf}	0.04^{kf}	0.11	0.01^{kf}	0.04^{kf}
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, 1, 1)$	0.06	0.06	0.13	0.08	0.06
$(\varepsilon_M, \varepsilon_D, \varepsilon_Q) = (\frac{1}{10}, \frac{4}{3}, 1)$	0.08	0.08	0.18	0.04	0.08

Notes A "kf" indicates the usage of the Kalman filter to infer the ω productivity shocks.

data from 1972 (instead of 1997, as in the benchmark calculations) to infer the steady-state relevant parameters Γ_{IJ}^M, μ_J, α_J, and ξ_J.[30]

For the fifth column, in the data generating process, I replace factor-neutral productivity shocks in the government industry with government demand shocks (online Appendix F.8 spells out the solution of the model filter with demand shocks; see in particular Equation 73). For all other industries, I retain TFP shocks instead of demand shocks. The rationale behind this robustness check stems from the application of military spending shocks as a source of identifying variation for ε_M and ε_Q in Section II. Up to now, our model filter has precluded these types of shocks. So, the final column of Table 4 checks whether the misspecification, which comes about because of the omission of military spending shocks, is quantitatively important. It is not.

Table 5 presents the relative importance of sectoral shocks for various values of ε_X and ε_{LS}. In the specifications in which ε_M and ε_D both equal 1, industry-specific shocks contribute between 18 and 23 percent of aggregate volatility. In contrast, so long as $\varepsilon_M = 0.1$, industry-specific shocks account for at least half of GDP volatility with $\varepsilon_D \in \{2/3, 1, 4/3\}$.

As a third set of robustness checks, I examine the contribution of sectoral shocks to aggregate fluctuations in different countries. For this analysis, I employ data from the EUKLEMS database, which describes industries' output growth rates for a range of developed countries between 1970 and 2007 (see online Appendix C for a description of the dataset). As I estimate in online Appendix D, industries' input choices and input prices, using the World Input Output Tables, suggest the elasticity

[30] The Capital Flows data necessary to construct Γ_{IJ}^X are unavailable for 1972. For this reason, I use the 1997 Capital Flows Table to infer the Γ_{IJ}^X for the robustness check corresponding to the penultimate column of Table 4.

TABLE 5—ROBUSTNESS CHECKS: R^2(*sectoral shocks*) AND $\bar{\rho}(\omega)$ FOR DIFFERENT VALUES OF ε_D AND ε_M

ε_X	1	1	1	1	$\frac{3}{5}$	$\frac{4}{5}$	$\frac{6}{5}$
ε_{LS}	2	$\frac{1}{2}$	1	4	2	2	2
R^2(sectoral shocks)							
$(\varepsilon_M, \varepsilon_D) = (1, 1)$	0.21^{kf}	0.18^{kf}	0.20^{kf}	0.23^{kf}	0.23^{kf}	0.22^{kf}	0.21^{kf}
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, \frac{2}{3}\right)$	0.99^{kf}	0.99^{kf}	0.99^{kf}	0.99^{kf}	0.96^{kf}	0.98^{kf}	1.00^{kf}
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, 1\right)$	0.83	0.78	0.81	0.92	0.97	0.86	0.81
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, \frac{4}{3}\right)$	0.59	0.51	0.55	0.62	0.65	0.62	0.56
$\bar{\rho}(\omega)$							
$(\varepsilon_M, \varepsilon_D) = (1, 1)$	0.19^{kf}	0.22^{kf}	0.21^{kf}	0.18^{kf}	0.18^{kf}	0.19^{kf}	0.20^{kf}
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, \frac{2}{3}\right)$	0.04^{kf}	0.04^{kf}	0.04^{kf}	0.04^{kf}	0.03^{kf}	0.04^{kf}	0.04^{kf}
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, 1\right)$	0.06	0.06	0.06	0.08	0.05	0.05	0.06
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{10}, \frac{4}{3}\right)$	0.08	0.09	0.08	0.07	0.07	0.07	0.08

Notes: Throughout the table, $\varepsilon_Q = 1$. A "kf" indicates the usage of the Kalman filter, as opposed to direct application of equation (11), to infer the ω productivity shocks.

TABLE 6—ROBUSTNESS CHECKS: R^2(*sectoral shocks*) AND $\bar{\rho}(\omega)$ FOR DIFFERENT VALUES OF ε_D AND ε_M

Country	Denmark	Spain	France	Italy	Japan	Netherlands
R^2(sectoral shocks)						
$(\varepsilon_M, \varepsilon_D) = (1, 1)$	0.63^{kf}	0.87^{kf}	0.80	0.47	0.07	0.44
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, \frac{2}{3}\right)$	0.87	1.00	1.00	0.89	0.61	0.81
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, 1\right)$	0.80	0.98^{kf}	1.00	0.84	0.30	0.72
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, \frac{4}{3}\right)$	0.76^{kf}	0.96^{kf}	1.00	0.79	0.79	0.64
$\bar{\rho}(\omega)$						
$(\varepsilon_M, \varepsilon_D) = (1, 1)$	0.08^{kf}	0.08^{kf}	0.10	0.13	0.34	0.11
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, \frac{2}{3}\right)$	0.02	0.02	0.05	0.06	0.07	0.03
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, 1\right)$	0.02	0.04^{kf}	0.09	0.12	0.17	0.05
$(\varepsilon_M, \varepsilon_D) = \left(\frac{1}{3}, \frac{4}{3}\right)$	0.04^{kf}	0.05^{kf}	0.13	0.17	0.07	0.07

Notes: Throughout the table, $\varepsilon_Q = 1$. A "kf" indicates the usage of the Kalman filter, as opposed to direct application of equation (11), to infer the ω productivity shocks.

of substitution among intermediate inputs may be higher for these six countries than are in Table 1, while the elasticity of substitution between intermediate inputs and value added may be lower. For this reason, in Table 6, I choose a somewhat higher value of ε_M, $1/3$ instead of 0.1. As with the US data, correlations among productivity shocks tend to be lower, and the assessed role of industry-specific shocks are higher, in specifications with lower values of the preference and production elasticities of substitution. For five of these six foreign countries, the sole exception being Japan, industry-specific productivity shocks account for at least half of aggregate volatility with $\varepsilon_M = 1/3$.

In online Appendix E, I demonstrate that the benchmark results are robust to (i) the de-trending method, (ii) the period length, (iii) censoring outlier observations, (iv) looking at different parts of the sample separately (excluding the Great

Recession, or looking at the first half and second half of the sample separately), and (v) modeling the durability of consumption goods.

IV. Conclusion

In the short run, industries have limited ability to substitute across their inputs. This paper extends a standard multi-industry real business cycle model to explore the role of limited substitutability on the assessed role of sectoral shocks. A worked out example of this elaborate model indicates that observed relationships among industries' output growth rates could either be rationalized with high elasticities of substitution in production (or preferences) along with correlated shocks, or with low elasticities and uncorrelated shocks. Using data on industries' input choices and their input prices, I estimate that production elasticities of substitution are, on balance, small. As a result, I find that sectoral shocks are more important than previously thought. Whereas previous assessments of multi-sector real business cycle models—based on unitary elasticities of substitution across inputs and consumption products—have concluded that industry-specific shocks account for less than half of aggregate volatility, the current paper indicates that sectoral shocks are the primary source of GDP fluctuations.

Appendix

Details of the US Data.—This section clarifies the sample construction and defines the variables used to estimate the model's elasticities of substitution. The main data sources are the 1997 to 2013 "Use" tables and the 1997 "Make" and Capital Flows tables, all from the Bureau of Economic Analysis; and Dale Jorgenson's KLEMS dataset.

Table A1 characterizes the way in which I classify industries. The NAICS codes refer to those in the Annual IO Tables. The third through fifth columns of Table A1 give the cost shares of capital, labor, and intermediate inputs. These are computed from the BEA GDP by Industry dataset. The intermediate input cost share is computed as the ratio of intermediate input expenditures relative to total gross output. The labor share is the ratio of labor compensation to total gross output. The remainder defines the capital cost share. The final column of Table A1 gives the consumption expenditure share of each industry. The consumption expenditures are taken from the BEA 1997 Input-Output Table, as sales to the following industry codes: F010 (Personal consumption expenditures), F02R (Residential private fixed investment), and F040 (Exports). To compute consumption expenditures by the government sector, I combine F06C (Federal national defense: Consumption expenditures), F07C (Federal national nondefense: Consumption expenditures), and F10C (state and local: consumption expenditures). With the aim of improving the numerical performance of the model filter, in my calibrations of ξ, I bound the preference weights, from below, at 0.006.

Section II's analysis requires information on purchases across industries, the prices of each industry's good, and the prices of each industry's intermediate input bundle. For each year between 1997 and 2013, the Annual IO Tables contain information

Table A1—Industry Definitions, Factor Shares, and Preference Weights

#	Name	NAICS	Capital	Labor	Interm. inputs	Consumption
1	Agriculture, forestry	11	0.32	0.10	0.58	0.008
2	Mining	212	0.23	0.25	0.52	0.001
3	Oil and gas extraction	211, 213	0.40	0.18	0.42	0.000
4	Construction	23	0.16	0.32	0.52	0.036
5	Food and kindred products	311, 312	0.14	0.12	0.74	0.043
6	Textile mill products	313, 314	0.08	0.23	0.69	0.003
7	Apparel, leather	315, 316	0.09	0.22	0.69	0.017
8	Lumber	321	0.09	0.22	0.69	0.002
9	Furniture and fixtures	337	0.13	0.31	0.56	0.004
10	Paper and allied products	322	0.16	0.21	0.63	0.003
11	Printing and publishing	323, 511	0.18	0.29	0.53	0.009
12	Chemicals	325	0.27	0.16	0.58	0.020
13	Petroleum refining	324	0.21	0.06	0.73	0.009
14	Rubber and plastics	326	0.15	0.22	0.63	0.004
15	Non-metallic minerals	327	0.21	0.26	0.53	0.001
16	Primary metals	331	0.09	0.19	0.71	0.002
17	Fabric. metal products	332	0.16	0.29	0.54	0.003
18	Non-electrical machinery	333	0.11	0.27	0.62	0.009
19	Electrical machinery	335	0.18	0.24	0.58	0.005
20	Motor vehicles	3361–3363	0.11	0.15	0.74	0.024
21	Other transport. equip.	3364–3369	0.10	0.30	0.60	0.008
22	Instruments	334	0.19	0.24	0.56	0.021
23	Misc. manufacturing	339	0.21	0.32	0.47	0.009
24	Warehousing	48, 49	0.18	0.33	0.49	0.024
25	Communications	512, 513, 514	0.34	0.22	0.44	0.021
26	Electric/gas utilities	22	0.51	0.17	0.32	0.019
27	Wholesale and retail	42, 44, 45	0.32	0.38	0.30	0.117
28	F.I.R.E.	52-53, HS, OR	0.51	0.15	0.33	0.170
29	Other services	54-56, 60-89	0.18	0.43	0.38	0.250
30	Government	G	0.15	0.54	0.31	0.159

on the value of commodities that are used by different industries. The output price of each industry is taken from the BEA GDP by Industry dataset, using the Fisher ideal price index to aggregate up to the classification in Table A1. To compute each industry's intermediate input price, I follow a similar procedure. For each downstream industry, I require information on changes in its intermediate input bundle's price, for each year (this variable appears on the right-hand side of equation (13)). I use the Fisher ideal price index to compute change in the intermediate input prices:

$$\Delta \log P_{t+1,J}^{in} = \sum_{I=1}^{30} \frac{P_{tI} M_{t,I\to J} + P_{t+1,I} M_{t+1,I\to J}}{\sum_{I'=1}^{30} P_{tI'} M_{t,I'\to J} + P_{t+1,I'} M_{t+1,I'\to J}} \cdot \Delta \log P_{t+1,I},$$

where, as in Section I, $M_{t,I\to J}$ represents the physical units of intermediate inputs from industry I to industry J, and P_{tI} denotes the unit price of industry I's output. For each downstream industry, J, I compute the change in its intermediate input price—between years t and $t+1$—as the weighted average in the changes in the prices of the supplying industries, I, with the weights set at the year t and $t+1$ share of J's intermediate input purchases that come from industry I.

To construct Γ^M and Γ^K, I use data from the 1997 Input Output Table and Capital Flows Table. I make two adjustments to the 1997 Capital Flows Table when producing Γ^K. First, government investment is not measured in the Capital Flows Table. As a result, I need to apply information from the Input Output Table, which *does* contain sales to the government investment industry. These are measured as sales to the following industries: F06S, F06E, and F06N (Investment in Federal Defense); F07S, F07E, and F07N (Investment in Federal Nondefense); F10S, F10E, and F10N (Investment in State and Local Government). Second, ones needs to account for maintenance and repair expenditures, which are not included in the Capital Flows Table. As McGrattan and Schmitz (1999) report, maintenance expenditures are sizable, potentially accounting for 50 percent of total physical capital investment. Foerster, Sarte, and Watson (2011) use this finding as motivation for adding to the diagonal entries of Γ^K. I add a 35 percent share to the diagonal entries of Γ^K to account for these maintenance and repair expenditures. This augmentation presumes that capital-good repairs draw on within-industry resources (e.g., firms that produce a product use their own inputs to repair their capital equipment).[31]

For the robustness check on good durability, performed in online Appendix Table 15, the set of durable goods are those designated as such by Basu, Fernald, and Kimball (2006), plus the construction industry: construction, lumber, furniture and fixtures, non-metallic minerals, primary metals, fabricated metal products, non-electrical machinery, electrical machinery, motor vehicles, other transportation equipment, instruments, and miscellaneous manufacturing.

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