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The Heterogeneous Business-Cycle Behavior of Industrial Production

Jackson Evert and Felipe Schwartzman

Industry-level data can provide a window into the sources of business cycles as well as propagation mechanisms. This is because depending on what determines those, one might expect different industries to behave differently. One notable example of the use of industry-level data for that purpose is Gertler and Gilchrist (1994), who pointed to the relatively larger impact of monetary shocks in industries with relatively smaller sized firms as evidence for the role of financial frictions in propagating those shocks. Another example is Bils et al.'s (2013) comparison of markup fluctuations in durable vs. nondurable sectors as a means to assess whether demand fluctuations could cause fluctuations in markups.

The use of industry-level variation can also provide advantages over the use of even more disaggregated firm-level data. First, since industries are to a large extent defined by the nature of their products, differences between industries are more plausibly determined by stable differences in technology and preferences than differences across firms within an industry. Second, because industry-level data already allow for some aggregation, they capture at least part of the general equilibrium effects that are likely to be important at the aggregate level. Third, industry-level data are more readily available, allowing for a useful first pass before acquiring harder-to-obtain firm-level data. The clear disadvantage is that because industries are different from one

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another along several dimensions, one needs to be always concerned about the possibility that industry variation is driven by some omitted characteristic. Thus, any work using industry-level data must incorporate extensive controls.

The purpose of this article is to present some stylized facts for how the business-cycle behavior of sectoral output differs with sectoral characteristics. Those stylized facts can be informative either as a means to determine sources of fluctuations and transmission channels or as indications of important sources of sectoral heterogeneity that ought to be controlled for in any study that attempts to uncover those sources and channels. We construct these stylized facts by first calculating standard business-cycle statistics such as relative volatility and correlation with GDP for each of the seventy-two sectors for which industrial production data are available separately. With those statistics in hand, we can then ask which industry-level characteristics are most likely to predict how these moments vary.

The measures of sectoral characteristics we focus on fall into four categories. The first category includes determinants of the demand for products in different sectors. Those may be informative about the role of fluctuations in the composition of demand for different types of products on business cycles. For example, the extent to which sectors that have the government as a main customer fluctuate more or less with aggregate GDP provides some information about the role of government consumption in business cycles (Ramey [2011] provides a recent review of the literature). The second category includes determinants of production costs. Those can provide a window into the role of cost fluctuations in business cycles. For example, a wide literature has pointed to energy cost fluctuations as an important driver of business cycles (see Hamilton [2003] for a seminal example). Variables in the two categories, demand and cost, can provide information about the role of the integration of different industries in production chains. This can help shed light on theories of business-cycle propagation that emphasize the input-output structure of the economy, such as Acemoglu et al. (2012). The third category includes measures of pricing distortions, including measures of market power and of price stickiness. Those can shed light on theories of business cycles that emphasize markup fluctuations as a key propagation mechanism (Rotemberg and Woodford [1999] provide a review). The fourth category includes firm-level characteristics that the literature has pointed to as correlated with sensitivity to financial frictions. Those are relevant for theories of business cycles that emphasize financial shocks and financial frictions (Bernanke and Gertler 1989; and Kiyotaki and Moore 1997). Those different categories are constructed in order to obtain a wide scope of cross-industry differences that the existing literature has pointed out as potentially important.

Some of the most salient findings are as follows:

1) Industries that are more oriented toward the production of consumer goods, which produce goods that are nondurable, and that produce necessities tend to be less volatile and less correlated with business cycles than other industries. Furthermore, they also tend to lead them. A similar pattern is present in firms that intensively use agricultural inputs.

2) Industries that are more oriented toward the production of goods consumed by the government are less correlated with business cycles relative to other industries and tend to lag business cycles. At the same time, industries that are more oriented toward the private sector tend to lead business cycles.

3) Industries in which nominal prices change infrequently tend to lag business cycles.

4) Industries whose characteristics are likely to be correlated with sensitivity to financial frictions are likely to lag business cycles, whereas those that are less likely to be exposed to those frictions tend to lead them.

5) The position of different industries in the production chain matters. Industries that are highly integrated in the production chain either by being intensive in the use of intermediate inputs or by dedicating a large fraction of their output to intermediate inputs are more likely to lead GDP.

The first section provides a more careful description and justification of the methodology. The subsequent section represents the core of the paper. First, it presents a description of how the different moments are distributed across sectors. Then, in four subsections we provide more detail on the findings for each of the four categories described above and provide some discussion of those findings in light of existing literature. After those, we perform a multivariate analysis to account for the fact that industry characteristics might be correlated among themselves. The last section summarizes the results. In the Appendix, we present a detailed description of how we constructed the various measures of industry characteristics.

1. METHODOLOGICAL DETAILS

In this section, and in all sections that follow, we will examine statistics for detrended time series. The detrending process follows Hodrick and Prescott (1997) and involves fitting a curve through the time series that strikes a balance between staying close to the data and remaining relatively smooth.[1] This trade-off is controlled by a parameter that, in one extreme, makes the estimated trend perfectly smooth and, hence, linear and, on the other extreme, leads to an estimated trend that is identical to the data. The commonly used parameter for quarterly data is 1600. The detrended series is then the log difference between the series and the estimated trend. In what follows we refer to a moment as being a "business-cycle" moment whenever it is constructed using HP-filtered time series.

In order to gather a better understanding of how different moments provide different information about the comovement of sectoral output and business cycles, consider first the following model of detrended sectoral output in which, for simplicity, we abstract from dynamics:

$$Y_{i,t} = \sum_{r=1}^{R} \lambda_{i,r} \epsilon_{r,t},$$

where $Y_{i,t}$ is output in sector i, $\epsilon_{r,t}$ are the values at time t of each of R shocks potentially affecting all sectors, and $\lambda_{i,r}$ is the sensitivity of sectoral output to each of the aggregate shocks. Shocks $\epsilon_{r,t}$ are uncorrelated with one another, i.e., $cov(\epsilon_{r,t}, \epsilon_{r',t}) = 0$ for all $r \neq r'$ and all t. Note that this specification is quite flexible, since we do not restrict R to be a small number relative to the number of sectors. In particular, the shocks $\epsilon_{r,t}$ can include idiosyncratic shocks, i.e., shocks that affect only one sector. It also accommodates setups in which shocks that affect primarily one sector also affect other sectors through input-output linkages, etc.[2] For simplicity, assume that detrended aggregate output can be approximated as a simple average of sectoral output, so that

$$Y_t = \sum_{i=1}^{I} \frac{Y_{i,t}}{I}.$$

The simplest moment of interest is the business-cycle variance of sectoral output relative to that of aggregate GDP. If we normalize the variance of the aggregate shocks $\epsilon_{r,t}$ to 1, this is

[1] As a robustness test, we also generated the tables using a Band-Pass filter (see Baxter and King [1999] for details on that kind of filtering). They are available upon request.

[2] See Acemoglu et al. (2012) for analytical and quantitative explorations. We refer the reader to these papers for further details. For the purposes of this essay, one can accommodate that view by reinterpreting some of the aggregate shocks as shocks that affect primarily particular sectors but do not "wash out" in aggregate due to linkages.

$$\frac{std(Y_{i,t})}{std(Y_t)} = \sqrt{\frac{\sum_{r=1}^{R} \lambda_{i,r}^2}{\sum_{r=1}^{R} (\sum_{i=1}^{I} \lambda_{i,r}/I)^2}}$$

or, more compactly,

$$\frac{std(Y_{i,t})}{std(Y_t)} = \sqrt{\frac{\sum_{r=1}^{R} \lambda_{i,r}^2}{\sum_{r=1}^{R} \bar{\lambda}_r^2}},$$

where $\bar{\lambda}_r \equiv \sum_{i=1}^{I} \lambda_{i,r}/I$ is the average sensitivity of sector i to aggregate shock r. In this benchmark case, the relative variance of a sector is large if $\lambda_{i,r}^2$ is on average large relative to $\bar{\lambda}_r^2$. Note that this measure does not allow us to distinguish whether the large relative variance stems from a relatively large sensitivity to shocks that are also important for other sectors (i.e., $\lambda_{i,r} > \bar{\lambda}_r >> 0$) or from a high sensitivity to a shock that is not relevant for other sectors (i.e., $\lambda_{i,r} > \bar{\lambda}_r \simeq 0$). The latter case would correspond to a case in which sector-specific shocks are very large for individual sectors as compared to aggregate shocks but "wash-out" in aggregate.

The correlation of industrial output with GDP provides an alternative view on the cyclical sensitivity of a sector. If business cycles were predominantly caused by a single common shock to all sectors, with sector-specific shocks playing a very small role, one would expect the correlation of all sectoral output with aggregate GDP to be very close to one. Contrariwise, if sectoral shocks play a disproportionate role in individual sector output, one would expect the correlation of that sector with GDP to be relatively smaller. Similarly, one may find small correlations if output in a given sector is driven by an aggregate shock that is not the main driving force of aggregate business cycles. In terms of our simple model with $I \to \infty$, the correlation between any given sector and aggregate output is

$$corr(Y_{i,t}, Y_t) = \frac{\sum_r \lambda_{i,r}\bar{\lambda}_r}{(\sum_r \lambda_{i,r})^2(\sum_r \bar{\lambda}_r)^2}.$$

If $\lambda_{i,r}$ and $\bar{\lambda}_r$ have mean zero, the correlation between $Y_{i,t}$ and Y_t would be simply given by the correlation between between $\lambda_{i,r}$ and $\bar{\lambda}_r$. More generally, it is an increasing function of that correlation. Thus, the correlation between sectoral output and aggregate output measures the extent to which the two are driven by the same shocks.

Note that it is possible for the output of a given industry to be at the same time much more volatile than aggregate output and to have a low contemporaneous correlation. This would happen if such an industry's output is largely determined by idiosyncratic shocks, which have little effect on the output of other industries. Conversely, an industry might be less volatile than aggregate output but also highly correlated if it is mostly driven by the same shock that drives other industries but is comparatively less sensitive to those.

Finally, apart from relative variances and correlation with GDP, we also provide statistics for the correlation of sectoral output and leads and lags of output. Interpreting those requires a dynamic model. This is a straightforward generalization of the model described above, in which industrial output depends on shocks that occurred in the past:

$$Y_{i,t} = \sum_{s=0}^{\infty} \sum_{r=1}^{R} \lambda_{i,r,s} \epsilon_{r,t-s},$$

where we now also impose that $cov(\epsilon_{i,t}, \epsilon_{j,t-s}) = 0 \ \forall i, j, s$; that is, we impose that shocks are i.i.d., with all persistence a function of $\lambda_{i,r,s}$. The model above is fairly general, as it corresponds to a moving average representation of a vector-valued time-series model (see, for example, Hamilton [1994] for a detailed discussion).

Note that under this more general framework, it is possible for two variables to be contemporaneously uncorrelated even if they are driven by the same shock, so long as that occurs at different lags. For example, if $Y_{i,t} = \epsilon_{1,t}$ and $Y_{i*,t} = \epsilon_{1,t-1}$, those two processes will have zero contemporaneous correlation. However, the correlation of $Y_{i,t}$ and $Y_{i*,t+1}$ will be equal to one. More generally, examining lead and lagged correlations may provide us with some indication of whether certain industries are more likely to respond more sluggishly with shocks than overall GDP, a fact that is likely to be reflected in relatively low contemporaneous correlations by relatively high correlations with lagged output. Conversely, examining correlations with leads and lags of output may provide us a sense of variables that react more rapidly to shocks, thus forecasting output.

2. THE CROSS-SECTORAL DISTRIBUTION OF BUSINESS-CYCLE MOMENTS

Table 1 shows some descriptive statistics for the distribution of various business-cycle moments across sectors. The first observation is that in all sectors, business-cycle variance is larger than that of aggregate output, and for the median sector it is four times as large. This observation is consistent with the notion that output in individual sectors is largely

Table 1 Summary Statistics

	Variance	Mean	Median	25th Percentile	75th Percentile
Std. Dev.	3.38	3.93	4.03	2.54	4.80
t-8	0.03	-0.21	-0.23	-0.31	-0.12
t-6	0.03	-0.07	-0.08	-0.21	0.04
t-4	0.04	0.15	0.14	0.02	0.27
t-3	0.04	0.28	0.26	0.13	0.45
t-2	0.05	0.40	0.40	0.23	0.57
t-1	0.06	0.49	0.54	0.33	0.69
t	0.07	0.53	0.63	0.32	0.74
t+1	0.06	0.47	0.53	0.30	0.69
t+2	0.05	0.36	0.39	0.18	0.54
t+3	0.04	0.24	0.25	0.08	0.41
t+4	0.04	0.14	0.14	0.00	0.28
t+6	0.03	0.00	0.00	-0.16	0.15
t+8	0.03	-0.11	-0.13	-0.24	0.02

Note: The cells refer to descriptive statistics of moments across industries. For each industry, we calculate a standard deviation and correlations with leads and lags of output. We then report statistics summarizing the cross-industry distribution of those moments.

driven by idiosyncratic shocks that are to a large extent averaged out in aggregate.

The second observation is that the correlation of sectoral output with aggregate GDP is mostly positive (animal food manufacturing and dairy product manufacturing being the only sectors with a negative correlation). The median sector has a correlation of 0.63 with GDP, and 75 percent of the sectors have a correlation of more than 0.32.

Third, the median correlation with leads and lags of GDP declines as the number of leads or lags increase in a fairly symmetrical fashion. At six-quarter leads and lags, the median sector has a correlation with output that is fairly close to zero. In the next subsection, we will describe how those business-cycle moments correlate with various measures of industry characteristics.

Demand

We start our investigation of stylized facts by examining how business-cycle moments depend on determinants of sectoral demand. There is no a priori reason why the demand for different products should vary in the same way with business cycles. In fact, sectoral variation in sensitivity to different demand components can provide a way to test theories of propagation of demand shocks. For example, Bils et al.

(2013) use cross-industry variation in sensitivity of demand as a means to assess the ability of demand shocks to lead to markup variations.

It is a well-known stylized fact of business cycles that consumption of nondurable goods varies less than output over the business cycle, whereas the demand for durable consumer goods and investment goods varies more than output. This suggests that sectors whose production is more dedicated to consumption ought to experience relatively lower business-cycle variation. We check whether this simple prediction is true by constructing for each sector a measure of the importance of household consumption in its output. Roughly speaking, it corresponds to the share of the output of each industry that is purchased by households as consumer goods (see Appendix for a detailed discussion of how this and other measures are constructed). As we can observe, the prediction is born out by the data, with consumption-oriented sectors exhibiting lower business-cycle variance, although the negative correlation is relatively small in absolute value. Interestingly, however, the *correlation* of sectoral output with the business cycle also declines with its orientation toward household consumption. This suggests that compared to other sectors, sectors oriented toward household consumption are more likely to be driven by shocks other than the ones determining overall GDP. Interestingly, the pattern disappears and, in fact, reverses itself once one compares business-cycle fluctuations at the sectoral level with that of future GDP. It appears that, relatively speaking, household consumption-oriented sectors tend to *lead* business cycles. This may imply some ability on the part of households to forecast business cycle shocks and adjust their consumption accordingly early on.

Bils et al. (2013) focus on durability of the goods produced in different sectors as a major source of variation in sensitivity to demand shocks. Demand for durable goods is particularly sensitive to shocks because stocks of durables are much larger than purchases in any given period, so large changes in those purchases are necessary in order to change the stock in use. More concretely, suppose a car depreciates at a rate δ, and aggregate household demand for cars is given by $X_{car,t}$. For simplicity of exposition, suppose demand follows an exogenous process. Then, if demand for cars increases by 1 percent, this requires increasing the stock of cars in circulation by 1 percent. However, if we take a stable demand for cars as a baseline, households must increase their purchase of cars from $\delta X_{car,t}$ (the amount that they need to purchase in order to make up for depreciation) to $(\delta + 0.01)X_{car,t}$, an increase of $1/\delta$ percent. Thus, if cars depreciate at a rate of 5 percent per quarter, this implies an increase in car purchases of 20 percent. Consistently with those calculations, output volatility does seem to be tightly linked to the durability of the good produced in a given sector.

Figure 1 Demand Correlates

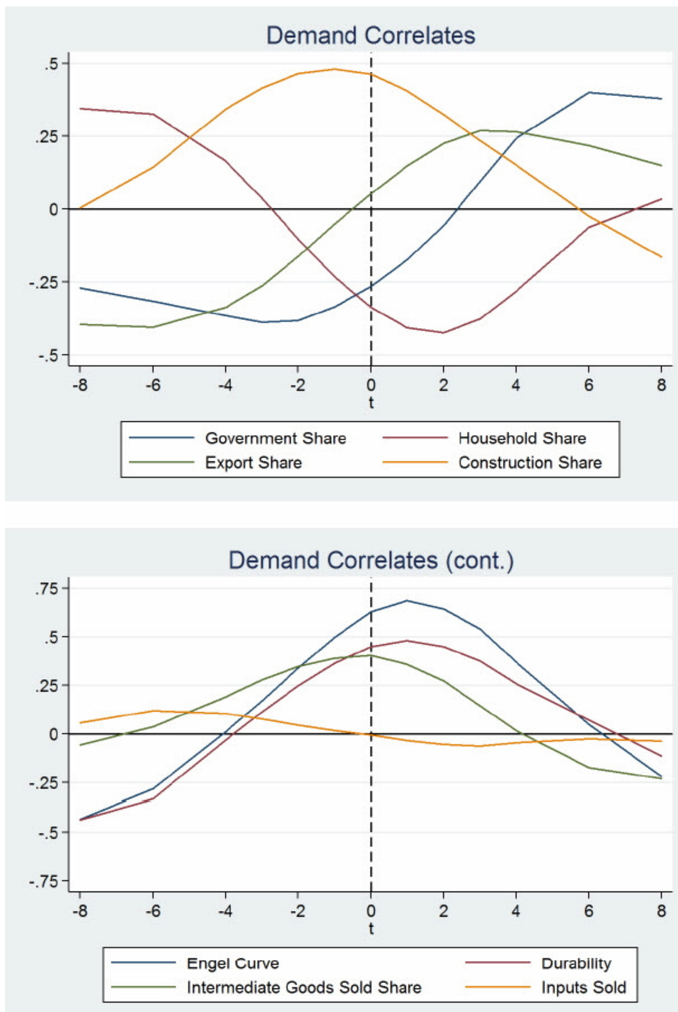


Table 2 Demand Correlates

	Std. Dev.	t-8	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+8
Household Share	-0.19	0.35	0.16	0.04	-0.1	-0.23	-0.34	-0.41	-0.43	-0.38	-0.28	0.03
Government Share	-0.04	-0.27	-0.37	-0.39	-0.38	-0.34	-0.26	-0.18	-0.06	0.09	0.24	0.38
Construction Share	0.02	0.00	0.34	0.41	0.46	0.48	0.46	0.4	0.32	0.23	0.15	-0.17
Export Share	0.36	-0.4	-0.34	-0.26	-0.16	-0.05	0.05	0.15	0.22	0.27	0.26	0.15
Intermediate Share	-0.15	-0.06	0.19	0.28	0.34	0.39	0.40	0.36	0.27	0.14	0.02	-0.23
Inputs Sold	-0.27	0.05	0.1	0.08	0.04	0.02	-0.01	0.04	-0.05	-0.06	-0.04	-0.04
Engel Curve	0.45	-0.44	0.01	0.17	0.34	0.5	0.63	0.68	0.64	0.54	0.37	-0.22
Durability	0.62	-0.44	-0.03	0.11	0.25	0.36	0.45	0.48	0.45	0.38	0.26	-0.12

Note: Table reports the correlations between industry characteristics and business-cycle moments (either relative volatility or business-cycle correlation for various industry leads/lags).

The findings for the correlation between depreciation and various moments largely resemble those for household consumption orientation, with sectors producing more durable goods being more contemporaneously correlated with GDP and less-durable sectors leading aggregate GDP. The main difference between the two measures is that durability is a much better predictor of the relative volatility of different sectors than consumption orientation.

Another household-demand-related dimension that one might expect to be predictive of the sensitivity of output in different sectors to business-cycle variations is the income elasticity of demand for that good (or the slope of the Engel Curve). Bils et al. (2013) estimate this elasticity using cross-sectional data. Using their estimates, we find that sectors with steeper Engel Curves are also more volatile and more correlated with output. The result is interesting in that it suggests that business-cycle variation in national income has a qualitatively similar impact on household demand composition as variation in income across households at a given point in time. It is also noteworthy that necessary goods (i.e., those with low income elasticity) are particularly good predictors of business cycles. Those goods also tend to be more household-oriented and have higher depreciation rates. Interestingly, the magnitude of the correlations between Engel coefficients and output correlations stands out when compared to the other metrics.

Given the focus of much of business-cycle analysis on the role of fiscal shocks, one further demand-side related metric of interest is orientation of a given sector toward government consumption. That metric is especially interesting since it provides a window into the role of fiscal shocks in driving sectoral output. Sectors oriented toward government consumption do not appear to be more or less volatile than other sectors. However, they are less contemporaneously correlated with business cycles, as one would expect if government purchasing decisions were largely disconnected from broader economic conditions. Interestingly, however, they become more correlated with lags, implying that the impact of shocks affecting output in most sectors only affect those that are oriented toward government consumption with delay.

The orientation of individual industries toward construction provides a further dimension of industry demand that is likely to be informative about theories of the business cycle. We find that those sectors do tend to be more correlated with business cycles, in line with theories that have gained prominence after the Great Recession, consistent with housing demand playing a prominent role in driving business-cycle fluctuations. Furthermore, they appear to lead business cycles slightly.

A further source of industry-level variation is motivated by recent work on the interplay between industry-level and aggregate dynamics, which has emphasized the importance of input-output linkages in the propagation of shocks. This suggests that it could be interesting to investigate whether industry-level business-cycle moments correlate with a measure of how "upstream" an industry is, meaning what fraction of its output is sold as inputs to other industries. We find that such industries, while not more or less volatile than others, tend to be more correlated with business cycles. They also are slightly more correlated with future output than with past output, hinting at timing delays between the production of intermediate inputs and final outputs.[3]

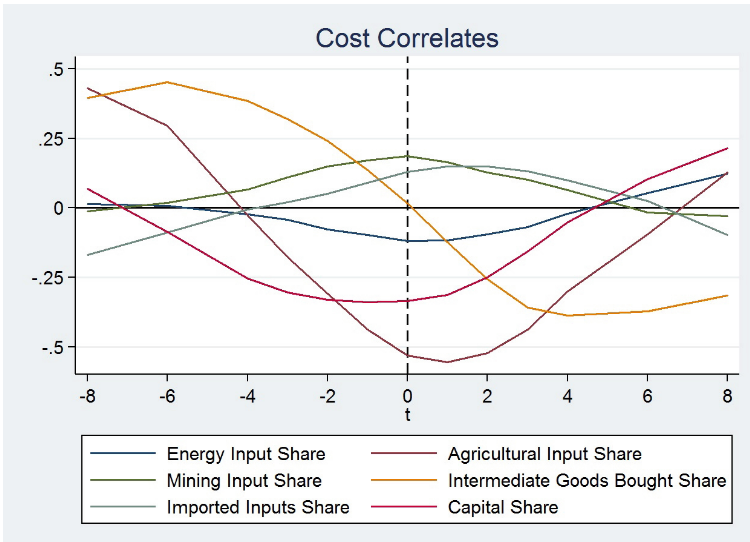
Finally, we investigate the extent to which the foreign orientation of a sector makes it more or less correlated with business cycles. We find that sectors that are less export-oriented tend to lead the business cycle relative to sectors that are more export-oriented. Thus, export-oriented sectors appear to be more insulated from business-cycle shocks in early stages.

Cost

We now turn to measures capturing the intensity of use of different inputs in production. We start by focusing on those input categories that are likely to have the most volatile prices, including energy, food, and mining. To the extent that industries that are intensive in those inputs are correlated with business cycles, this may indicate that shocks to the supply of these inputs may help drive business-cycle fluctuations. Of those three, the one that appears to have the most predictive power over industry-level business-cycle statistics is the fraction of agricultural inputs used in production. However, rather than implying that

[3] Following Acemoglu et al. (2012), we also examine the role, if any, of heterogeneity in industry "degree," as measured by the fraction of industry intermediate input production in total production of intermediate inputs in the economy. For that measure, we did not find that this has any predictive impact on business-cycle moments.

Figure 2 Cost Correlates



Note: Figures report the correlations between industry characteristics and business-cycle moments (either relative volatility or business-cycle correlation for various industry leads/lags).

agricultural cost shocks drive business cycles, the main finding is that industries intensive in agricultural inputs appear to be more *disconnected* from business cycles, with contemporaneous correlations being smaller the more agricultural inputs are used. Interestingly, however, their volatility is also relatively smaller. Industries with agricultural inputs also tend to lead business cycles, in a pattern reminiscent of low Engel elasticity sectors. This occurs in part because sectors that use agricultural goods in production are in part producing exactly such necessities. The multivariate analysis in Section 2.5 should help us disentangle those effects.

Table 3 Cost Correlates

	Std. Dev.	t-8	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+8
Energy Inputs	-0.24	0.01	-0.02	-0.04	-0.08	-0.1	-0.12	-0.12	-0.1	-0.07	-0.02	0.12
Agricultural Inputs	-0.36	0.43	-0.03	-0.18	-0.31	-0.44	-0.53	-0.55	-0.52	-0.44	-0.3	0.13
Mining Inputs	0.04	-0.01	0.07	0.11	0.15	0.17	0.19	0.16	0.13	0.1	0.06	-0.03
Intermediate Inputs	0.00	0.39	0.38	0.32	0.24	0.14	0.02	-0.12	-0.26	-0.36	-0.39	-0.32
Imported Inputs	0.30	-0.01	0.15	0.15	0.16	0.16	0.16	0.13	0.07	0.01	-0.04	-0.22
Imp. Share of Inputs	0.32	-0.17	-0.01	0.02	0.05	0.09	0.13	0.15	0.15	0.13	0.1	-0.1
Capital Share	-0.18	0.07	-0.25	-0.3	-0.33	-0.34	-0.33	-0.31	-0.25	-0.16	-0.05	0.21

Comparatively speaking, sectors with high intensity in energy and mining inputs do not seem to be more or less correlated with business cycles than other sectors. The low correlation with energy intensity is somewhat surprising in light of the common notion that energy shocks are an important source of business-cycle fluctuations. We also examine what happens when we eliminate the three industries with the highest use of energy inputs, since those have a level of energy use that is much higher than the others and are themselves involved in energy production. Eliminating those sectors does not increase the extent to which business-cycle correlations are associated with energy use.[4]

We also investigate whether capital intensity and intermediate input intensity are predictive of business-cycle correlations. Capital-intensive sectors appear to be less correlated with business cycles contemporaneously but more correlated after eight quarters. This suggests a sluggish response of those sectors to business-cycle shocks in line with capital-adjustment costs and planning lags.

Furthermore, we examine the correlation between the fraction of intermediate inputs in total output and business cycles. We find that sectors that use more intermediate inputs are no more or less correlated with business cycles than sectors that use fewer intermediate inputs. However, they do tend to lead business cycles, whereas sectors that use proportionately less intermediate inputs tend to lag business cycles.

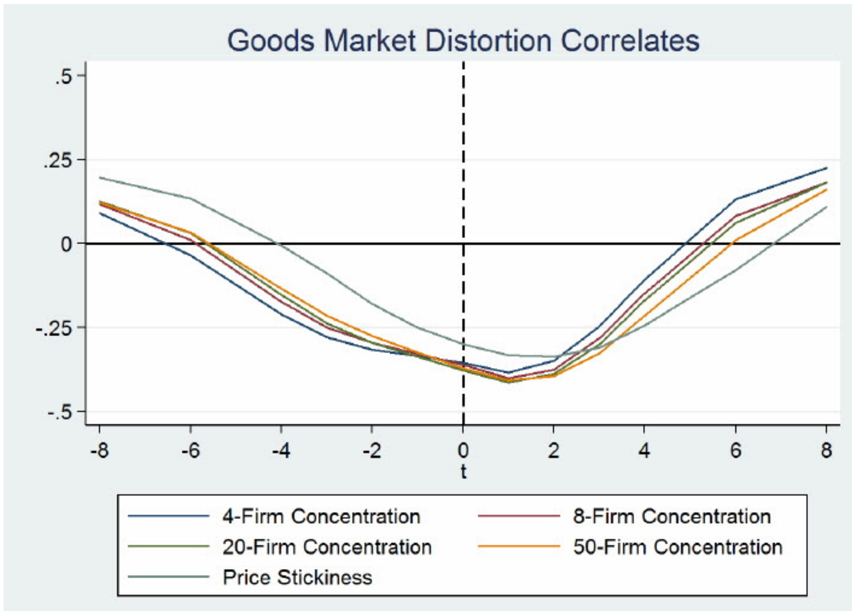
Lastly, we investigate how the use of imported inputs affects business-cycle moments. We find that sectors with a high share of imported inputs are also relatively more volatile. This is in line with the notion that the price of imported inputs is likely to be more volatile since part of that is tied to exchange rate fluctuations. At the same time, we find that the share of imported inputs is not predictive of business-cycle correlations.

Goods Market Pricing Distortions

The third category of industry characteristics that we examine are those capturing goods market distortions. One measure attempts to capture the competitive pressures faced by firms in different industries, the idea being that firms in more concentrated industries have more scope to vary their markups over the business cycle. The second one is a measure of nominal stickiness based on microeconomic price data. Bils et al. (2014) have defended time-varying goods market distortions as a

[4] For brevity, we do not report the numerical results for these exercises. The removed sectors are i) electric power generation, transmission and distribution; ii) oil and gas extraction; iii) natural gas distribution; and iv) petroleum and coal manufacturing.

Figure 3 Goods Market Distortion Correlates



Note: Figures report the correlations between industry characteristics and business-cycle moments (either relative volatility or business-cycle correlation for various industry leads/lags).

key element in business-cycle propagation. As for nominal rigidities, they of course underlie a large literature on monetary policy and business cycles. To measure those, we use the average frequency of price adjustment as measured in the CPI data by Nakamura and Steinsson (2008).

We first examine how market concentration in different industries is related to their business-cycle behavior. We measure market concentration by the share of the top four firms in each industry. This provides a measure of the potential role for goods market pricing distortion under the assumption that firms in more concentrated industries have more scope for markup variation. We find that firms in more concentrated industries are also less cyclical.

Table 4 Goods Market Distortion Correlates

	Std. Dev.	t-8	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+8
Four-Firm Concentration	0.11	0.09	-0.21	-0.28	-0.32	-0.33	-0.36	-0.38	-0.35	-0.25	-0.11	0.23
Eight-Firm Concentration	0.07	0.12	-0.17	-0.25	-0.3	-0.33	-0.36	-0.4	-0.38	-0.28	-0.15	0.18
20-Firm Concentration	0.02	0.13	-0.15	-0.24	-0.29	-0.34	-0.38	-0.41	-0.39	-0.3	-0.17	0.18
50-Firm Concentration	-0.01	0.12	-0.14	-0.21	-0.27	-0.32	-0.37	-0.41	-0.39	-0.33	-0.21	0.16
Price Stickiness	-0.08	0.2	-0.01	-0.09	-0.18	-0.25	-0.30	-0.33	-0.34	-0.31	-0.24	0.11

We then examine the correlation of business-cycle statistics with the average frequency of price changes. The data indicate that industries with less sticky prices (higher frequency of price adjustment) are less correlated with business cycles. This is in line with the view that nominal rigidities play a role in the propagation of business-cycle shocks.

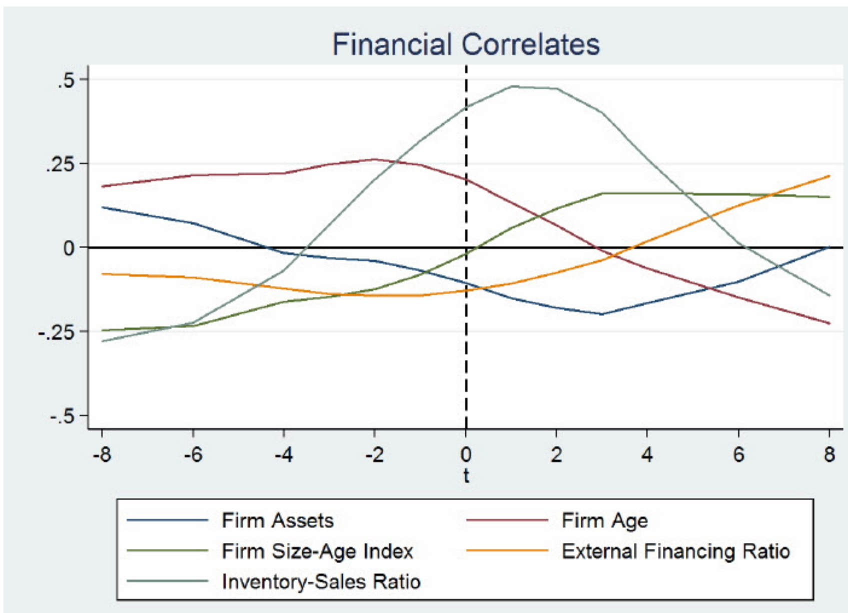
Financial Sensitivity

The last category we measure includes the industry characteristics that are likely to be correlated with their sensitivity to financial shocks. The most prominent one is average firm size, proposed by Gertler and Gilchrist (1994), under the idea that smaller firms are more likely to be financially constrained. We also examine firm age and a financial frictions index proposed by Hadlock and Pierce (2010) using both size and age. Two further measures of financial sensitivity are external financial dependence, proposed by Rajan and Zingales (1998) to study the role of financial development in growth, and the inventory/sales ratio, used by Schwartzman (2014), Raddatz (2006), and others to study the impact of financial shocks in less-developed economies.

We find that industries with smaller firms (and, presumably, facing higher financial frictions) tend to lag business cycles by about three quarters, but even there, the correlation is relatively moderate. On the other hand, older firms (which presumably face lower financial frictions) tend to lead business cycles. The net effect is that the size-age index implies that industries in which financial constraints are less severe lead business cycles, whereas those where they are more severe lag business cycles. This pattern does not suggest a simple story of financial frictions amplifying business cycles, but it does suggest some possibly interesting implications for the role of financial frictions in their propagation. Of course, this interpretation presumes that susceptibility to financial constraints is the major difference between firms of different ages and sizes. Presumably, those characteristics might be correlated with many other aspects of firm behavior.

A similar pattern is apparent when we use external financial dependence as a measure of sensitivity to financial conditions. External financial dependence is equal to one minus the median ratio between cash flow and capital expenditures for firms within an industry. It measures how much firms need to raise over and above their internally generated cash flow in order to finance their typical investment. We find that fluctuations in industries in which firms are more dependent on external finance are more likely to lag fluctuations in output.

Figure 4 Financial Correlates



Note: Figures report the correlations between industry characteristics and business-cycle moments (either relative volatility or business-cycle correlation for various industry leads/lags).

Table 5 Financial Correlates

	Std. Dev.	t-8	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+8
Assets	-0.13	0.12	-0.02	-0.03	-0.04	-0.07	-0.11	-0.15	-0.18	-0.2	-0.17	0.00
Age	-0.12	0.18	0.22	0.25	0.26	0.25	0.20	0.13	0.07	-0.01	-0.06	-0.22
Size-Age Index	0.12	-0.25	-0.16	-0.15	-0.12	-0.08	-0.02	0.06	0.12	0.16	0.16	0.15
Ext. Fin. Ratio	-0.08	-0.08	-0.12	-0.14	-0.14	-0.14	-0.13	-0.11	-0.07	-0.04	0.02	0.21
Cash Flow	-0.08	0.24	-0.14	-0.2	-0.23	-0.26	-0.27	-0.29	-0.26	-0.2	-0.12	0.13
Capital Exp.	0.01	0.26	0.01	-0.06	-0.1	-0.15	-0.20	-0.26	-0.29	-0.28	-0.22	-0.03
Invt.-Sales Ratio	0.25	-0.28	-0.07	0.07	0.2	0.32	0.42	0.48	0.47	0.4	0.26	-0.14

The final industry characteristic we examine is the inventory/sales ratio. In contrast to the other measures, the business-cycle correlation for firms with a high inventory/sales ratio is fairly large. It is also particularly pronounced contemporaneously, although the peak occurs at one- or two-quarter lags.

Multivariate Analysis

The analysis so far is based off the comparison of business-cycle moments across industries taking one industry characteristic at a time. To disentangle those, we turn now to multivariate analysis, i.e., we run a simple OLS regression with the different business-cycle statistics as a dependent variable and all the industry characteristics that we explored on the right-hand side. Here we use the measure of energy intensity after excluding the four outlying sectors. This sharpens the interpretation of the results since, as pointed out by Bils et al. (2013), those very high energy intensity sectors are also sectors with very flexible prices, leading to a strong multicolinearity between energy intensity and frequency of price changes. This multicolinearity problem is eliminated once we exclude those outliers. Tables 6 and 7 present the results for the different statistics, with coefficients that are significant at a 10 percent level marked in bold. Before running the regression, all right-hand-side variables were normalized by their standard deviation, so the coefficients can be interpreted as the effect of a one standard deviation change in the value of those regressors on the various business-cycle statistics. Focusing on these statistically significant coefficients, we obtain the following results, which are robust to the introduction of multivariate controls:

1) *Volatility is higher in sectors with durable goods, imported inputs, and high frequency of price adjustment.*

The findings for durable goods and imported inputs conform to the findings from the univariate analysis above. The correlation with frequency of price adjustment only emerges in the context of the multivariate analysis. It conforms to the notion that, all else constant, firms in industries that are subject to more variable shocks will choose to adjust prices more frequently.

2) *The sectors least correlated with aggregate GDP are those producing necessities (low Engel elasticity), those that have their production oriented toward government consumption, and those that intensively use agricultural and mining inputs. Sectors oriented toward the production of intermediate inputs are more correlated with output.*

Table 6 Regression Coefficients (1)

	Std. Dev.	t-8	t-6	t-4	t-3	t-2	t-1
Four-Firm Concentration Ratio	-0.117	0.002	-0.006	-0.032	-0.043	-0.044	-0.034
Durability	**0.655**	-0.051	**-0.068**	-0.058	-0.053	-0.046	-0.033
Energy Inputs	-1.663	-0.065	-0.056	-0.079	-0.099	-0.108	-0.093
Ext. Fin. Ratio	-0.126	-0.005	-0.009	-0.024	-0.029	-0.03	-0.032
Household Share	-0.137	0.033	**0.049**	**0.048**	0.035	0.016	-0.01
Government Share	**-0.382**	-0.037	**-0.060**	**-0.083**	**-0.089**	**-0.093**	**-0.090**
Construction Share	-0.406	0.015	0.03	0.045	**0.058**	**0.073**	**0.086**
Inv.-Sales Ratio	0.077	-0.043	**-0.058**	**-0.061**	-0.047	-0.031	-0.01
Median Assets	0.397	-0.022	-0.033	-0.018	-0.001	0.016	0.021
Median Age	-0.357	0.021	0.031	0.025	0.027	0.029	0.03
Engel Curve	0.004	-0.002	0.044	0.063	0.071	**0.083**	**0.099**
Agricultural Inputs	-0.373	0.026	0.023	-0.035	**-0.062**	**-0.080**	**-0.094**
Mining Inputs	0.443	**0.125**	0.087	0.048	0.018	-0.015	-0.047
Intermediate Inputs	-0.128	0.036	0.057	**0.078**	**0.078**	**0.073**	0.062
Imported Inputs	**0.980**	0.037	0.056	0.056	0.056	0.058	0.051
Capital Share	-0.034	0.015	-0.004	-0.005	-0.007	-0.008	-0.017
Price Stickiness	**0.971**	0.037	0.038	0.057	0.074	0.076	0.07

Note: Tables report OLS coefficients for business-cycle moments against the set of industry characteristics. Coefficients significant at the 10 percent level are in bold. Each column is a separate regression.

The multivariate analysis suggests that the low correlation of sectors intensive in agricultural inputs is not a simple artifact of those sectors also being oriented toward household consumption.

The last two facts concern the dynamic relationships between sectoral output and aggregate output:

3) *Sectors that are oriented toward the private sector (have a low government share), that sell a large fraction of their output as intermediate inputs, use fewer agricultural inputs, use intermediate inputs intensively, adjust prices frequently, and are not dependent on external finance tend to lead business cycles.*

and

4) *Sectors that are government-oriented, sell a small fraction of their output as intermediate inputs, are not intensive in mining inputs, adjust prices less frequently, and are more dependent on external finance tend to lag business cycles.*

Table 7 Regression Coefficients (2)

	t	t+1	t+2	t+3	t+4	t+6	t+8
4-firm Concentration Ratio	-0.031	-0.035	-0.027	-0.01	0.012	0.046	0.051
Durability	-0.021	-0.013	-0.007	0.001	0.015	0.046	0.054
Energy Inputs	-0.067	-0.018	0.036	0.087	0.136	**0.182**	**0.150**
Ext. Fin. Ratio	-0.028	-0.026	-0.018	-0.008	0.008	0.03	0.035
Household Share	-0.034	**-0.058**	**-0.068**	**-0.061**	-0.042	-0.005	0.002
Government Share	**-0.075**	**-0.054**	-0.03	-0.001	0.029	**0.061**	**0.063**
Construction Share	**0.082**	**0.058**	0.033	0.013	0.001	-0.011	-0.01
Inv. Sales Ratio	0.018	0.037	0.045	0.043	0.036	0.02	0.011
Median Assets	0.024	0.028	0.022	0.008	-0.003	-0.027	-0.026
Median Age	0.026	0.013	0.005	0.003	0.005	0.006	-0.01
Engel Curve	**0.108**	**0.095**	0.063	0.034	0.009	-0.036	-0.06
Agricultural Inputs	**-0.086**	**-0.065**	-0.039	-0.012	0.011	0.022	0.044
Mining Inputs	-0.086	**-0.131**	**-0.162**	**-0.177**	**-0.172**	-0.117	-0.069
Intermediate Inputs	0.036	-0.002	-0.039	-0.059	-0.059	-0.049	-0.061
Imported Inputs	0.050	0.04	0.032	0.018	-0.002	-0.055	**-0.085**
Capital Share	-0.019	-0.019	-0.019	-0.015	-0.012	-0.009	-0.012
Price Stickiness	0.048	0.005	-0.048	-0.095	**-0.135**	**-0.146**	-0.082

Note: Tables report OLS coefficients for business-cycle moments against the set of industry characteristics. Coefficients significant at the 10% level are in bold. Each column is a separate regression.

Those two latter sets of facts add some interesting details to the first two. For example, it becomes clear that having demand oriented toward government consumption does not insulate a sector's output from business cycles but rather leads it to react with a lag. It is also interesting to note that sectors that are very integrated in the production chain (in the sense of using intermediate inputs intensively) tend to lead business cycles, whereas those that do not use as many intermediate inputs tend to lag. The relatively low correlation of sectors with high financial dependence also hides the fact that they respond with a lag. Finally, the regressions also point to an early response of flexible price sectors and a delayed response of sticky price sectors.

3. CONCLUSION

We asked a simple question: How do business-cycle statistics vary with sectoral characteristics? Some of the answers were predictable, others less so. The results highlight the promise and pitfalls of using industry-level data to identify driving forces and propagation mechanisms in business cycles. On the one hand, the results help focus the analysis on channels that are more likely to be relevant and take away from others that do not appear so relevant. For example, the analysis points to pricing and financial frictions as channels worth investigating but provides very little evidence of a prominent role for oil shocks. On the other hand, the results highlight the need to interpret results with care, since differences in business-cycle behavior between industries may be dominated by differences in durability or demand composition that may be correlated with other characteristics of interest.

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APPENDIX

A.1 List of Industries

Our industrial classification is primarily based on the four-digit 2007 NAICS codes, with certain four-digit industries consolidated into a single category to facilitate the construction of either the PCE/industry crosswalk or the industry controls. The full list of industries used is displayed in Table 8.

A.2 PCE/Industry Crosswalk

We use the 2007 PCE Bridge Table published by the Bureau of Economic Analysis to match PCE expenditure categories to industries. The Bridge Table contains consumer spending levels by PCE category and commodity pairs. For each pair, the level of total spending going to producers, wholesalers, retailers, and transport is provided.

Also included in the Bridge Table file is a concordance of commodity categories with NAICS codes. This allows the commodities to be matched with our industry groups. However, this concordance is less granular in many cases than our industry classification—these industries are pooled for the purposes of constructing the PCE/industry crosswalk. In addition, while the analysis in the paper focuses predominantly on manufacturing and related sectors, for the purpose of constructing this crosswalk, it is important to capture all sectors of the economy in order to construct a more detailed PCE/industry crosswalk. For this purpose, we make use of all the commodities and industries present in the Bridge Table.

Using this commodity/NAICS concordance with the expenditure data in the bridge table, we obtain expenditure estimates for producer margins by PCE category and industry. No observations for the wholesale, retail, or transport industries exist, as their expenditure is contained in the corresponding wholesale, retail, and transport margins for each PCE/industry pair. To create observations for these industries, we total the entire margin across a given PCE category and use this total as the value for that PCE/industry category pair. For instance, we total all wholesale margins across the "auto leasing" PCE category, and this is taken as the value for the wholesale/auto leasing pair. We do this for each PCE category and for wholesale, retail, and transport.

For these, we sum the total wholesale margin across all industries for a given PCE category and construct an additional observation designating the total as the expenditure for a given PCE category and wholesale industry pair. We repeat this process for all PCE categories and do the same for retail and transport as well.

Given total consumer expenditure broken down by PCE category/ industry pairs, we construct a crosswalk between the two categories using expenditure share weights. This allows the translation of some set of values at the PCE level to the industry level, or vice versa. For each PCE/industry pair, the crosswalk contains two weights; one is the proportion of the total industry expenditure that is also from the PCE category, and the other is the proportion of total PCE category expenditure that is also from the industry. The former is used to translate PCE-level data to the industry level and the latter from the industry to the PCE level.

As an example of how this occurs, consider a set of data at the industry level with one value per industry. This dataset is merged with the crosswalk so that now each PCE category/industry pair contains both the expenditure-share weights and the industry-level data value. The PCE-level data are then estimated as the weighted average for the PCE category across all industries. This provides an estimate of the PCE value by imputing the data from the constituent industries that make up the PCE category. Using the other weight that exists for each PCE category/industry pair, the same process can occur in reverse, with PCE data translated to the industry level.

Note that, as stated above, some industries do not have a unique commodity code in the original Bridge Table and were thus pooled for the construction of the crosswalk. For these industry groups, the crosswalk will provide a single value for the group rather than a separate value for each industry. In these cases, we assume that all industries share this value in common.

A.3 Controls

A.3.1 Concentration Ratios

Industry-concentration data are taken from the 2007 Economic Census. For each 2007 NAICS industry at the six-digit level, the census contains the percentage of total industry sales from the largest four, eight, twenty, and fifty firms, along with total industry revenue. We match each six-digit NAICS category to the industry in which it is contained and take the revenue-weighted mean across all six-digit NAICS within the industry as the concentration ratio for that industry. This provides a four-firm, eight-firm, twenty-firm, and fifty-firm concentration ratio for each of our industries.

For robustness, we construct additional concentration measures from the same data: in addition to taking the revenue-weighted mean, we also take both the median and the maximum concentration ratio across six-digit NAICS industries. This leaves us with twelve values, corresponding to either four, eight, twenty, or fifty-firm concentration ratios, and to either the mean, median, or maximum across subindustries.

A.3.2 Durability

The BEA publishes depreciation/durability estimates for consumer durables, equipment, and structures. We match each PCE category to a durable good, equipment, or structure category if a corresponding category exists. We then take the service life estimate published by the BEA as a measure of the durability of the item. Nondurable goods are assigned a durability of zero. Values are then translated to the industry level using the PCE category/industry crosswalk.

A.3.3 Inputs

From the 2007 Benchmark Input/Output Use Table, we calculate the exposure of an industry to energy, agriculture, mining, as well as the industry's use of intermediate inputs. Using the commodity/NAICS crosswalk provided with the Use Table, we match each commodity to its corresponding industry and aggregate the Use Table to our industry classification. Where the provided concordance is not granular enough for our industry classification, we pool industries and assign the corresponding values to all industries in the group.

Energy Inputs: We take the proportion of total intermediate inputs that are from (1) electrical power generation, (2) oil and gas extraction, (3) natural gas distribution, and (4) petroleum and coal products manufacturing as a measure of each industry's energy exposure.

Agricultural Inputs: We take the proportion of total intermediate inputs that are from (1) crop production, (2) animal production and aquaculture, and (3) support activities for agriculture and forestry as a measure of each industry's exposure to agriculture.

Mining Inputs: We take the proportion of total intermediate inputs that are from (1) metal ore mining and (2) nonmetallic mineral mining and quarrying as a measure of each industry's exposure to mining.

Total Intermediate Inputs: We construct a measure of the total intermediate inputs used by the industry by taking the ratio of all industry inputs to the industry's output.

A.3.4 Capital Share

Also from the Use Table, we estimate the relative intensity of capital as opposed to labor in each sector. As for the input measures, we first aggregate the Use Table to our industrial classification. To do so, we compute the ratio of gross operating surplus over the sum of gross operating surplus and compensation to employees.

A.3.5 Output Shares

Again from the Use Table, we estimate several measures related to the destination of each industry's output. As before, we aggregate the Use Table to our industry classification.

Household Output: We calculate the household share as the proportion of industry output that goes to PCE.

Government Output: We calculate the government share as the total output sold to all federal, state, and local government categories listed in the Use Table as a ratio to total industry output.

Construction Output: We calculate the construction share as the proportion of each industry's output that is purchased by the construction sector.

Total Intermediate Output: We construct the proportion of total industry output that was used as an intermediate inputs by any other industry. For robustness, we also take the raw number of intermediate inputs sold without normalizing by industry output.

A.3.6 Imports and Exports

The Use Table also contains information on imports and exports by industry and can therefore also be used to calculate several measures describing the international linkages of each sector.

Import Penetration: For each industry, we take the value of industry outputs that are imported into the United States and divide by total industry production plus imports minus exports. This provides the share of each industry's final goods sold domestically that were produced internationally.

Exports: We calculate the export ratio as the share of industry output that is exported.

Imported Inputs: To measure the level of input connections to foreign markets, we calculate the ratio between imported intermediate inputs to total industry output.

Imported Share of Inputs: As an alternative measure of the input connections to foreign markets, we calculate the ratio of the total industry inputs that are imported.

A.3.7 External Financing Ratio, Cash Flow, and Capital Expenditure

Using capital expenditure and cash flow by firm and year from Compustat for 1979 through 2015, we can construct the external financing ratio as in Rajan and Zingales (1998), as one minus the ratio between cash flow to capital expenditure. Matching each firm to an industry, we take the median capital expenditure value across firms for each industry and year. Then, we take the median again across years to obtain a single value for each industry. The same procedure is used to obtain a median cash flow and median capital expenditure value for each industry. Rajan and Zingales (1998) describe the construction of the cash flow variable in greater detail.

A.3.8 Inventory Sales Ratio

From Compustat we take firm-level data on annual inventories and total sales from 1979 through 2015. From this, we normalize inventories by total sales for each firm. Matching firms to industries, we then take the median value for each industry and year and then select the median across years as the final industry value.

A.3.9 Size-Age Index

To construct measures of industry-specific financial constraints, we follow Hadlock and Pierce (2010), who show that an index that is linear in firm age and quadratic in firm asset size can capture the degree of firm financing constraints. Specifically, the index is calculated as $-.737 * size + .043 * size^2 - .04 * age$. We calculate this index for each firm and year between 1979 and 2015. Matching firms to industries, we take the median for each industry/year pair and again for each industry. We do the same for asset size and age separately.

A.3.10 Luxury Goods

We construct two measures of the degree to which the outputs of each industry are luxury goods. First, we use BLS data from the Consumer Expenditure Survey, which details the consumption expenditures for various goods by income decile. Matching these expenditure categories with PCE categories, we construct estimates of expenditures for each PCE category for the fourth and sixth income deciles and take the ratio of these values as an estimate of the luxury status of a PCE category. We then use the PCE/industry crosswalk to map these values to the industry level.

As an alternate measure of the income elasticity of industry output, we also take the Engel Curve slopes estimated by Bils et al. (2013). They estimate these Engel Curve values for PCE categories, which we map into the industry level using our PCE/industry crosswalk.

A.3.11 Price Stickiness

To capture the frequency of price changes within an industry, we take the price-adjustment durations estimated by Nakamura and Steinsson (2008). The estimates are provided at the Entry Line Item (ELI) level. By using the ELI/PCE crosswalk provided by the BLS, we can transfer these ELI-level duration values to the PCE classification. For each PCE category, we assign the average of the duration values for the set of ELIs with which the PCE category is matched. Following this, we can match PCE-level values to the industry level using the PCE/industry crosswalk.

Table 8 Industries

Industry	2007 NAICS
Oil and gas extraction	211-
Coal mining	2121
Metal ore mining	2122
Nonmetallic mineral mining and quarrying	2123
Support activities for mining	213-
Electric power generation, transmission, distribution	2211
Natural gas distribution	2212
Animal food manufacturing	3111
Grain and oilseed milling	3112
Fruit and vegetable preserving and specialty food manufacturing	3114
Dairy product manufacturing	3115
Animal slaughtering and processing	3116
Bakeries and tortilla manufacturing	3118
Other food manufacturing	3119
Beverage manufacturing	3121
Tobacco manufacturing	3122
Textile mills and textile product mills	313-, 314-
Apparel, leather, and allied manufacturing	315-, 316-
Sawmills and wood preservation	3211
Veneer, plywood, engineered wood product manufacturing	3212
Other wood product manufacturing	3219
Pulp, paper, and paperboard mills	3221
Converted paper product manufacturing	3222
Printing and related support activities	323-
Petroleum and coal products manufacturing	324-
Basic chemical manufacturing	3251
Resin, synthetic rubber, artificial synthetic fibers and filaments manufacturing	3252
Pesticide, fertilizer, other agricultural chemical manufacturing	3253
Pharmaceutical and medicine manufacturing	3254
Paint, coating, and adhesive manufacturing	3255
Soap, cleaning compound, and toilet paper manufacturing	3256
Plastics product manufacturing	3261
Rubber product manufacturing	3262
Clay product and refractory manufacturing	3271
Glass and glass product manufacturing	3272
Cement and concrete product manufacturing	3273
Lime, gypsum and other nonmetallic mineral product manufacturing	3274, 3279
Alumina and aluminum production and processing	3313
Nonferrous metal (except aluminum) production and processing	3314
Foundries	3315
Forging and stamping	3321
Cutlery and handtool manufacturing	3322
Architectural, construction, and mining machinery manufacturing	3323
Hardware manufacturing	3325
Spring and wire product manufacturing	3326
Machine shops, turned product, screw, nut, bolt manufacturing	3327
Coating, engraving, heat treating, and allied activities	3328
Other fabricated metal product manufacturing	3329
Agricultural, construction, and mining machinery manufacturing	3331
Industrial machinery manufacturing	3332

Table 8 (Continued) Industries

Ventilation, heating, air conditioning, and commerical refrigeration equipment manufacturing	3334
Metalworking machinery manufacturing	3335
Engine, turbine, power transmission equipment manufacturing	3336
Computer and peripheral equipment manufacturing	3341
Communications equipment manufacturing	3342
Audio and video equipment manufacturing	3343
Semiconductor & other electronic component manufacturing	3344
Navigational, measuring, electromedical, and control instruments manufacturing	3345
Electric lighting equipment manufacturing	3351
Household appliance manufacturing	3352
Electrical equipment manufacturing	3353
Other electrical equipment and component manufacturing	3359
Motor vehicle manufacturing	3361
Motor vehicle body and trailer manufacturing	3362
Motor vehicle parts manufacturing	3363
Aerospace product and parts manufacturing	3364
Railroad rolling stock manufacturing	3365
Ship and boat building	3366
Other transportation equipment manufacturing	3369
Household and institutional furniture and kitchen cabinet manufacturing	3371
Medical equipment and supplies manufacturing	3391
Newspaper, periodical, book, and directory publishers	5111