Flexibility and Frictions in Multisector Models*

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Abstract

Cross-sectoral heterogeneity in sectoral bond spreads is related to sectoral elasticities of substitution in production. During the Great Recession, more flexible firms paid lower sectoral bond spreads, generated higher revenues, and held more working capital. A model consistent with these facts— input-output linkages, working capital constraints, and heterogeneous elasticities—predicts that sectoral distortions during the Great Recession generated an *efficiency wedge*—due to input misallocation—2.4 times larger than one with homogeneous production functions. In addition, our model predicts input-output connections amplified the Great Recession 2.3 times as much as one with homogeneous elasticities.

Keywords: Elasticity of substitution, credit spreads, working capital constraints
JEL Codes: E32, E23, E44

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1 Introduction

The standard narrative of the Great Recession is one where financial frictions and interconnected sectors translated a small shock to a relatively-unimportant sector—often argued to be an unexpectedly-large number of subprime mortgage defaults—into a large economy-wide decline in economic activity. Recent theoretical work has shown how productivity and financial shocks can be amplified and propagated by input-output connections.[1] Despite the increase interest in more disaggregated models of the macroeconomy, the literature has overlooked the potential importance of sectoral heterogeneity in production elasticities (flexibility) to understanding: i) the extent to which some sectors are more vulnerable to distortions; and ii) the propagation and amplification of sectoral distortions by means of input-output connections.

In this paper, we document the empirical relationship between sectoral elasticities of substitution in production and firm-level outcomes: credit spreads, revenues, and working capital. Our facts illustrate that financing constraints in the use of inputs were an important aspect of the Great Recession. To explain our findings we develop a model with input-output linkages, heterogeneous elasticities, and working capital constraints. We then study the macroeconomic implications of our model. Given a set of sectoral frictions, which we proxy using sectoral bond spreads, we find that not accounting for the heterogeneity in sectoral elasticities implies an important underestimation of the role of sectoral distortions and input-output linkages in amplifying the Great Recession.

To estimate sectoral elasticities, we extend the instrumental variables approach in Atalay (2017) using U.S. data on input shares and relative input prices for 66 non-government sectors. We note that, besides the estimation bias due to unobserved sectoral productivity, time-varying credit frictions generate a bias in the estimation of production elasticities. We correct for this endogeneity in relative input prices using two complementary approaches. First, we use military spending and lags of our endogenous variables as instruments. Second, we estimate our elasticities for the whole sample and for the sample that excludes the Great Recession, a period of time with especially tight credit.

Our IV approach at the sectoral level works best when using data before the Great Recession (1997-2007). If we use the entire sample (1997-2014), the housing sector and wholesale trade sector, for example, display implausible elasticity estimates. These results indicate

[1] See Horvath (2000), Foerster et al. (2011), Atalay (2017), Miranda-Pinto (2018b), Bigio and La'O (2016), Jones (2011), Baqaee and Farhi (2017b), Luo (2015), and Osotimehin and Popov (2017) for some important examples.

that the bias from sectoral distortions in the estimation of elasticities is not fully addressed by standard IV methods. Therefore, our benchmark elasticity estimates are obtained using instrumental variables for the period 1997-2007. Even though the bias from credit frictions seems to affect the level of the estimates, it does not appear to affect the ranking of sectoral elasticities. Therefore, many of our main results in the paper—in particular, the link between sectoral elasticities and firm-level outcomes—hold regardless of the method and sample we use to estimate elasticities.

We find substantial heterogeneity in sectoral elasticities of substitution; in particular, the elasticity of substitution between labor-capital and intermediate inputs (ϵ_Q), and the elasticity of substitution between different types of intermediate inputs (ϵ_M). Consistent with Atalay (2017) and Boehm et al. (2018), we find that ϵ_M is small for manufacturing and primary sectors. In contrast, service sectors display substantially larger substitutability between intermediates, with $\epsilon_M \geq 1$. Moreover, we uncover substantial heterogeneity in ϵ_Q, with service sectors also displaying systematically larger $\epsilon_Q (\geq 1)$.

We then show that sectoral elasticities of substitution between labor-capital and intermediate inputs (ϵ_Q) are systematically correlated with sectoral bond spreads, firm-level revenue, and firm-level working capital—as measured by current assets minus current liabilities—during the Great Recession. We estimate panel-fixed effect regressions to control for sectoral and firm-level time-invariant unobserved characteristics. To account for the generated regressor problem we use bootstrap techniques. We identify the relationship between "flexibility" (ϵ_Q) and firm level outcomes by interacting sectoral elasticities with two time-varying controls: i) a dummy variable that is 1 for the Great Recession period and 0 otherwise; and ii) firms' leverage, as measured by the ratio between firms' debt and total sales (or assets). We observe that sectors with "more flexible" technologies saw their spreads rise less on average during the Great Recession. More flexible firms also experienced higher revenues and higher working capital. We also observe important heterogeneity within manufacturing and service sectors.

We interpret these facts through the lens of a multisector model with sectoral linkages through intermediates, heterogeneous production elasticities, and working capital constraints. These constraints require input costs to be partially financed in advance using within-period loans collateralized by end-of-period sales.[2] The Lagrange multiplier on these constraints can

[2] Formally this arrangement is quite similar to 'Sudden Stop' models with flow constraints, as in Bianchi (2011) or Benigno et al. (2013). The assumption of sales being collateral for loans instead of the value of physical assets is consistent with the results in Li (2015), who finds that a model with heterogeneous firms and financial frictions matches firm dynamics facts of Japanese firms best if firms can pledge as collateral

be interpreted as a spread.[3] In a simple vertical two-sector model, we are able to analytically characterize the relationship between ϵ_Q and the frequency and severity with which sectoral constraints bind.

The relationship between ϵ_Q and the Lagrange multiplier of the constraint depends on a multiplicative "wedge" between the cost of value-added and intermediate inputs. This wedge depends on three factors: (i) the fraction of costs that must be paid in advance, (ii) the relative importance of intermediates to value-added, and (iii) the fraction of sales that can be pledged as collateral. If the wedge exceeds one for a particular input, then that input is more costly when the constraint is binding. To facilitate analytical results, we assume that the only value-added input is labor and that inputs either face the working capital constraint fully or not at all (the fraction that must be financed in advance is either zero or one).

We use our model to qualitatively explain our facts. If constraints are binding, and given sectoral input shares in the data, the model can generate the observed relationship between spreads and frictions, including the heterogeneity within manufacturing and service sectors, provided firms are constrained in the use of intermediates. If constraints are not binding, and given the observed evolution of the relative cost of intermediates and value-added, the model implies that high elasticity sectors ($\epsilon_Q > 1$) were more likely to become constrained in the use of labor, while low elasticity sectors ($\epsilon_Q < 1$) were more likely to become constrained in the use of intermediates.

Finally, we perform a quantitative exercise to assess the roles of sectoral flexibility, sectoral frictions, and input-output connections in amplifying the Great Recession. We calibrate our model using our estimated sectoral elasticities as well as the observed input-output shares and consumption shares in 2007. We proxy for financial shocks using sectoral bond spreads. Our results indicate that not accounting for sectoral heterogeneity in elasticities implies an important underestimation of the role of sectoral distortions and input-output linkages in amplifying the Great Recession. We show that the *efficiency wedge*, due to input misallocation, is substantially amplified (2.4 times) when upstream service sector have higher production flexibility, as we found in the data. We identify three flexible-upstream-service sectors—in real estate and professional services sectors—as responsible for the large *efficiency wedge* generated by sectoral distortions during the Great Recession.

Our paper contributes to a number of distinct fields. First, we provide new estimates of sectoral production functions suitable for use in multisector business cycle models. In

half of their one-year ahead earnings and one-fifth of their assets.

[3]We can show that these results can also be obtained in a model with an explicit upward-sloping interest rate schedule for loan rates; results available upon request. See also Bigio and La'O (2016).

particular, we are the first to note that manufacturing and service sectors have very different production technologies, and this fact turns out to matter for a number of questions beyond the ones we address here. For example, Miranda-Pinto (2018b) shows that heterogeneous production elasticities are crucial for replicating the cross-country correlations between GDP volatility and input-output linkages.

Second, our paper points out the importance of modeling the macroeconomy with sectoral heterogeneity in flexibility and sectoral financial distortions. Distinct from Bigio and La'O (2016), who also study the role of sectoral distortions, i) we provide sector-level and firm-level facts that validate the existence of sectoral distortions in the use of input during the Great Recession, and ii) we illustrate the quantitative importance of the *efficiency wedge* (input misallocation) instead of the labor wedge (distorted labor supply) highlighted by Bigio and La'O (2016). We also contribute to this literature by emphasizing that deviating from Cobb-Douglas technologies (Bigio and La'O (2016)) and common sectoral elasticities (Atalay (2017) and Baqaee and Farhi (2017a)) are both important for the measurement of the role of sectoral frictions and input-output linkages during the Great Recession.

Third, our model has important implications for sectoral policies. Sectoral distortions in the use of inputs and sectoral linkages imply the existence of significant pecuniary externalities due the presence of prices in the collateral constraints. Miranda-Pinto (2018a) and Liu (2017) study the policy implications of related models.[4]

2 Motivating facts

In this section, we motivate our research question by analyzing the evolution of sectoral bond spreads. We collect sectoral bond spread data from Gilchrist and Zakrajsek (2012). The GZ credit spread measures for each non-financial firm the arithmetic average of the difference between firm i bond yield and a hypothetical Treasury security of the same maturity, for all the unsecured bonds issued by firm i at quarter t. The average maturity of the corporate bonds in Gilchrist and Zakrajsek (2012) is 13 years. However, because of the cash flows generated by coupon payments, the average duration of these bonds is considerably shorter. The sectoral bond spreads is defined as the median spread of all firms in sector j at time t.

Table 2.1 reports the descriptive statistics of sectoral bond spreads, at the 3-digit NAICS classification, for 2007q1 and 2009q1. Spreads are countercyclical. We observe that during

[4] Liu (2017) studies which sectors should be subsidized in order to most reduce input misallocation, while Miranda-Pinto (2018a) studies different combinations of input subsidies that are able to fully undo sectoral distortions, by taking advantage of sectoral connections.

the first quarter of 2009, the median sectoral spread was 4.5 times larger than the median spread in the first quarter of 2007 (6.3% compared to 1.4%). Not only the median was substantially higher, but also the cross-sectoral dispersion of spreads. The standard deviation of sectoral spreads in the first quarter of 2009 was 7.5 times larger than what it was in the first quarter of 2007 (5.3% compared to 0.7%). Similarly, the interquartile range of spreads increased by 3.8 times, from 1.17% to 4.44%.

What can account for the large cross-sectoral heterogeneity in sectoral spreads during the Great Recession? Sectoral leverage could certainly be a potential answer. Table 2.1, rows 3 and 4, report the descriptive statistics of sectoral leverage, as measured by the corporate debt to sales (or assets) ratio. While we observe an increase in the median leverage ratio (from 1.24 to 1.72), we do not observe a clear increase in the cross-sectoral dispersion of leverage. While the standard deviation of sectoral leverage increases from 2.32 to 2.53, the interquartile range, indeed, declines from 1.56 to 1.44.

Table 2.1
Sectoral spreads and leverage (2007q1 and 2009q1)

	median	sd	min	p25	p75	max
Bond spreads 2007Q1	1.39%	0.71%	0.59%	0.99%	2.16%	3.85%
Bond spreads 2009Q1	6.27%	5.27%	2.32%	4.17%	8.61%	25.92%
Debt to sales 2007Q1	1.24	2.32	0.25	0.86	2.30	15.24%
Debt to sales 2009Q1	1.72	2.53	0.35	1.25	2.81	15.51%

Note: In this table, we report descriptive statistics of corporate bond spreads at the 3-digit NAICS industry classification (51 industries). Source: Gilchrist and Zakrajsek (2012).

In Sections 3 and 4, we show that the cross-sectoral variation in spreads during the Great Recession is related to sectors' production flexibility. We then complement our evidence by showing that other firm-level outcomes—such as revenues and working capital—relate to production flexibility in a similar way. In Section 5, we show that our facts can be interpreted as evidence that sectoral credit constraints in the use of inputs were an important aspect of the Great Recession. In Section 6, we then show that our model economy—with working capital constraints and heterogeneous production elasticities—predicts that input-output connections and heterogeneity in production flexibility played a crucial role in amplifying inputs misallocation during the Great Recession.

3 Theoretical framework

Suppose that sectoral production uses an aggregate of capital and labor (value added V_j) and an aggregate of intermediates (material input M_j) to produce a final good Q_j:

$$Q_j = Z_j \left(a_j^{\frac{1}{\epsilon_{Q_j}}} V_j^{\frac{\epsilon_{Q_j}-1}{\epsilon_{Q_j}}} + (1-a_j)^{\frac{1}{\epsilon_{Q_j}}} M_j^{\frac{\epsilon_{Q_j}-1}{\epsilon_{Q_j}}} \right)^{\frac{\epsilon_{Q_j}}{\epsilon_{Q_j}-1}}, \tag{1}$$

where $\epsilon_{Q,j}$ is the elasticity of substitution and is sector-specific. The sectoral total factor productivity is Z_j. The importance of labor in production is a_j. The material input bundle M_j is constructed using intermediates from all sectors:

$$M_j = \left(\sum_{i=1}^{N} \omega_{ij}^{\frac{1}{\epsilon_{M_j}}} M_{ij}^{\frac{\epsilon_{M_j}-1}{\epsilon_{M_j}}} \right)^{\frac{\epsilon_{M_j}}{\epsilon_{M_j}-1}}, \tag{2}$$

where ϵ_{M_j} is the elasticity of substitution between different material inputs, and ω_{ij} represents how important are intermediate inputs from sector i in the total cost of intermediates of sector j.

In addition, firms are constrained in the financing of inputs. The working capital constraints are

$$\theta_j^v P_j^v V_j + \theta_j^m \sum_{i=1}^{N} P_i M_{ij} \leq \eta_j P_j Q_j, \tag{3}$$

where θ_j^v and θ_j^m are the fraction of the value added cost (renting an office and wage bill, for example) and intermediate input (M_j) cost that must be paid in advance, respectively. Firms are constrained in obtaining external funds. In particular, firms in sector j can only borrow up to a fraction η_j of total revenue $P_j Q_j$.[5]

[5] A microfoundation for this constraint is detailed in Bigio and La'O (2016). Before production takes place, firms borrow from a competitive financial intermediary the amount of input expenses needed to produce. There is a limited commitment problem, since after sales firms can default on their debt without paying back to the intermediary. Therefore, firms are required to pledge a fraction of sales as collateral. If a firm does not repay, the financial intermediary seizes a fraction η_j of total sales. In an equilibrium without default, the incentive compatibility constraint implies that firms can externally borrow up to a fraction η_j of total sales.

3.1 Estimation of elasticities

The cost minimization conditions imply (see Appendix A for more details)

$$\Delta \log \left(\frac{P^M_{jt} M_{jt}}{P_{jt} Q_{jt}} \right) = \left(1 - \epsilon_{Q_j}\right) \Delta \log \left(\frac{P^M_{jt}}{P_{jt}} \right) + \left(\epsilon_{Q_j} - 1\right) \Delta \log Z_{jt} + \epsilon_{Q_j} \Delta \log \overline{\mu}_{jt} \tag{4}$$

and

$$\Delta \log \left(\frac{P_{it} M_{ijt}}{P^M_{jt} M_{jt}} \right) = \left(1 - \epsilon_{M_j}\right) \Delta \log \left(\frac{P_{it}}{P^M_{jt}} \right). \tag{5}$$

P_{jt} is the price of output produced in sector j and P^M_{jt} is the price index for the bundle of intermediates used as inputs by sector j. The first equation (4) identifies ϵ_{Q_j} by measuring the response of the share of intermediate expenditures in total revenue (which equals total expenditures given constant returns to scale) to a change in the relative prices, and the second equation (5) identifies ϵ_{M_j} by measuring the response of the share of intermediates from sector i used in sector j (compared to the total expenditure by sector j) to a change in the relative prices.

The term $\bar{\mu}_{jt}$ is a function of the Lagrange multiplier of the working capital constraint μ_{jt}, and the parameters of the working capital constraint θ^m_j and η_j. Combining equations (4) and (5) we have the model's implied equation to estimate ϵ_M and ϵ_Q jointly:

$$\Delta \log \left(\frac{P_{it} M_{ijt}}{P_{jt} Q_{jt}} \right) = (\epsilon_{M_j} - 1) \Delta \log \left(\frac{P^M_{jt}}{P_{it}} \right) + (\epsilon_{Q_j} - 1) \Delta \log \left(\frac{P_{jt}}{P^M_{jt}} \right) + (\epsilon_{Q_j} - 1) \Delta \log Z_{jt} + \Delta \log \bar{\mu}_{jt}. \tag{6}$$

The last two terms in Equation (6) are unobserved productivity and credit wedges. Time variation in both terms biases the estimation of elasticities by OLS. The literature typically emphasizes the role of unobserved productivity in this bias (such as Atalay (2017)). Here, we note that the estimation of sectoral elasticities is furthered biased by the presence of time-varying sectoral frictions in the use of inputs ($\bar{\mu}_{jt}$).[6] Given that our goal is to investigate the relationship between production flexibility and distortions, as measured by sectoral bond spreads, our next step is to estimate elasticities avoiding the bias generated by distortions in Equation (6).

[6] In Appendix D, we discuss more in detail the direction of the bias due to credit wedges. The bias depends on which inputs are constrained and the borrowing ability of a given sector.

3.1.1 Dealing with endogeneity

To deal with the endogeneity due to unobserved productivity and frictions, we follow two complementary approaches. The first approach is to use standard IV methods to estimate elasticities. The second approach is to estimate elasticities for the whole sample period (1997-2014) and only for the years before the Great Recession (1997-2007) where we expect the bias from binding sectoral constraints to be less severe.

We consider the instrument used in Acemoglu et al. (2015) and Atalay (2017), namely sectoral military spending.[7] Higher military spending in sector j, or in sectors that use the output of sector j output intensively, increases the demand for sector j's output and therefore increases the price. The assumptions implicit here are that military spending is orthogonal to changes in sectoral productivity and that spending only affects input shares through changes in the relative cost of inputs.[8]

Following Atalay (2017) we construct instruments for the output price of sector j (P_{jt}), the price of the intermediate input bundle of sector j (P^M_{jt}), and the price of the intermediate input from sector i (P_{it}) that is used in the production of sector j. To formally define the instrument, define S_{ji} as the share of sector j's output that is purchased by sector i. Our instruments are then

$$Military_{p_j,t} = \sum_i (I-S)^{-1}_{ji} S_{i,military} \cdot \Delta \log(\text{Military Spending}_t),$$

$$Military_{p_i,t} = \sum_j (I-S)^{-1}_{ij} S_{j,military} \cdot \Delta \log(\text{Military Spending}_t)$$

$$Military_{p^m_j,t} = \sum_i \frac{P_{ijt} M_{ijt}}{P^M_{jt} M_{jt}} \cdot Military_{p_i,t}.$$

The term $(I-S)^{-1}$ measures the sum of direct and indirect changes that occur due to network connections.[9] Changes in military spending on sector i's output can have important indirect effects on sector j's output demand if military industries (i) purchase a large fraction

[7] Acemoglu et al. (2015) do not precisely use military spending as an instrument but rather as a demand shock. Obviously the two interpretations are closely related.

[8] Peter and Ruane (2017) estimate ϵ_M using firm level data from Indian firms. To correct for the endogeneity in the estimation of elasticities, the authors use changes in tariffs as instrument. Unlike Atalay (2017), Peter and Ruane (2017) find that ϵ_M is substantially above one, which is likely a 'long run' elasticity; similar large long-run results can be found in the literature on the elasticity of substitution between capital and labor.

[9] Note that, unlike the well-known Leontief inverse matrix, this matrix does not account for indirect upstream links—that is, sectoral supplier importance—but instead captures only indirect downstream links. That is, it captures how important other sectors are for the demand of a given sector's output.

of sector i's output (large $S_{i,military}$) or (ii) sector i, directly or indirectly, purchases a large fraction of sector j's output (large $(I-S)^{-1}_{ji}$).

We also take advantage of the dynamic panel data and use 1 year and 2 year lags of our endogenous variables. As long as productivity changes are independent over time, lagged sectoral prices are uncorrelated with current productivity but are correlated with current sectoral prices.

To estimate the elasticities we follow Atalay (2017), but we allow for the elasticities to vary across sectors. We use the BEA annual Input-Output data for the period 1997-2007(2014). To start, there are 71 sectors of the economy (66 are non-government sectors).[10] The empirical counterpart of Equation (6) is

$$\Delta \log \left(\frac{P_{it} M_{ijt}}{P_{jt} Q_{jt}} \right) = \phi_t + \alpha_j \Delta \log \left(\frac{P^M_{jt}}{P_{it}} \right) + \beta_j \Delta \log \left(\frac{P_{jt}}{P^M_{jt}} \right) + \nu_{ijt}, \qquad (7)$$

where ϕ_t are year fixed-effects that control for aggregate shocks.[11] The error term is denoted by ν_{ijt}. We can obtain the elasticities as

$$\epsilon_{Q_j} = 1 + \beta_j$$
$$\epsilon_{M_j} = 1 + \alpha_j.$$

In our IV approach, we estimate α_j and β_j for each sector—or group of sectors—separately. Our OLS panel fixed-effect estimates for α_j and β_j—used in Appendix A for robustness—take advantage of the panel structure of our data and are obtained from interacting sectoral prices with sectoral dummies.

3.1.2 Common sectoral elasticities

Before reporting our estimated sectoral elasticities, and with the goal of comparing our results to previous literature, we first impose that all sectors have the same elasticities. We use military spending and lagged sectoral prices for our IV estimation. The panel fixed-effect regressions include all sectors, while the IV estimations exclude government sectors. In both cases, given that we assume $\alpha_j = \alpha$ and $\beta_j = \beta$ for all j, we can include buyer-seller fixed-effects to control for unobserved time-invariant factors.

[10] For each sector we keep the top 25 intermediate goods' supplier sectors. The results are similar when using the 20 or 30 suppliers.

[11] In Appendix A, we also report our *biased* panel fixed-effect estimated sectoral elasticities. In this case, we include buyer-seller fixed-effects that control for unobserved time-invariant intermediate-input trade partner relationships, such as market power.

Table 3.1
Elasticities 1997-2014

VARIABLES	(1) FE	(2) FE	(3) FE^{exc}	(4) IV	(5) IV	(6) IV^{exc}
$\epsilon_M - 1$	-0.60***	-0.67***	-0.37***	-0.82**	-0.99**	0.67**
	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)
$\epsilon_Q - 1$	-0.24**	-0.05	-0.01	0.83*	1.29**	2.08***
	(0.02)	(0.66)	(0.95)	(0.08)	(0.01)	(0.00)
Observations	28,398	28,398	28,000	23,098	23,098	22,750
Number of partner	1,775	1,775	1,750	1,650	1,650	1,625
Year FE	No	Yes	Yes	No	Yes	Yes
F Kleibergen-Paap				28.13	29.59	13.63
P-value Sargan test				0.06	0.14	0.00

P-value in parentheses. Stock-Yogo test critical value 10%: 13.43. *exc* excludes the Petroleum industry.

Columns 1 to 3 in Table 3.1 present the panel fixed-effect elasticity estimates, while columns 4 to 6 present the IV estimates. The results indicate that ϵ_M lies between 0.01 and 0.4, while ϵ_Q lies between 0.7 and 2.3. These numbers are similar to those found by Atalay (2017). Unlike Atalay (2017), who aggregates the BEA sectors to match the 29 non-government sectors in KLEMS, we use all of the 66 non-government sectors in the BEA. Keeping these sectors matters for the measurement of the elasticities in service industries. We have almost 40 different service sectors, while in KLEMS classification there are only 6 non-government service sectors, partly due to misclassification. For example, using KLEMS sectoral classification, the mining supporting services sector appears inside the mining sector (which is a primary sector). Our results show that service sectors generally have much higher sectoral elasticities than primary sectors, so this misclassification could be important.

Another difference from Atalay (2017) is that to control for firm specific relationships—for example, market power of downstream industries with respect to suppliers—we consider intermediate-input partner fixed-effects when estimating Equation (7). Furthermore, besides using military spending as an instrument, we use two lags of the endogenous relative sectoral prices. We show in Table 7.2 of Appendix A that after adding two lags of sectoral relative prices, the first stage results are stronger and the second stage results are more precise.[12]

[12] In Table 7.2 of Appendix A we compare the IV results using different set of instruments. While the IV point estimates are similar with the different set of instruments, when adding 2 lags of the endogenous variables, our first stage improves substantially – the F test for weak identification Kleibergen-Paap (2006) rk – and also the precision of our second stage estimated elasticities. This is not necessarily true when we

Column 6 reports the estimated elasticities excluding the Petroleum and Coal industry. The estimated elasticities, especially the IV ones, change considerably. The estimated elasticities are much larger, with ϵ_Q and ϵ_M being larger than one. The fact that the sole exclusion of the Petroleum and Coal industry substantially changes the estimated elasticities clearly motivates the point of our paper: assuming common flexibility across sectors is misleading.[13] While the IV estimates with common elasticities are reasonable and similar to previous papers, we will see in the next section that once we disaggregate, two key sectors that experienced large declines during the Great Recession, the housing and wholesale trade sectors, display implausible elasticities when including the Great Recession years, even when we use standard IV techniques. For this reason, our benchmark elasticity estimates only consider the period 1997-2007. However, as we show in Appendix E, the main results of the paper still hold with the IV estimates using the whole sample.

3.1.3 Sectoral elasticities

We now proceed to estimate sectoral elasticities using instrumental variables. Figure 1 plots the histogram of the estimates for the period 1997-2014. We report the distribution of the point estimates as well as the distribution of the point estimates plus two standard deviations of the estimates. Consistent with the aggregate estimates in Table 3.1, the estimates for ϵ_M are smaller than the estimates for ϵ_Q. On the other hand, for few sectors ϵ_Q is below zero even when considering the upper value of the 95% confidence interval of the estimate. In addition, there are a few sectors with estimates for ϵ_M and ϵ_Q that are much larger than one (such as the housing sector).

With the idea of avoiding the bias arising from binding sectoral constraints during the Great Recession, we next estimate the sectoral elasticities using only the period 1997-2007 (Figure 2). We still observe some negative estimates for ϵ_Q, but the distribution of ϵ_Q is more symmetric and centered around the mean compared to the sample 1997-2014. In particular, the housing sector does not display the large elasticity obtained using the whole sample. Clearly, the unusual response of housing during the Great Recession is distorting our estimates in important ways, which we interpret as evidence for the bias generated by financial constraints.

For a more detailed discussion on the validity and strength of our IV estimates we direct the reader to Appendix D, in particular, Figures 12 to 16.

estimate sectoral IV regressions.

[13] Young (2018) discusses the sensitivity of IV estimators to a wide variety of assumptions.

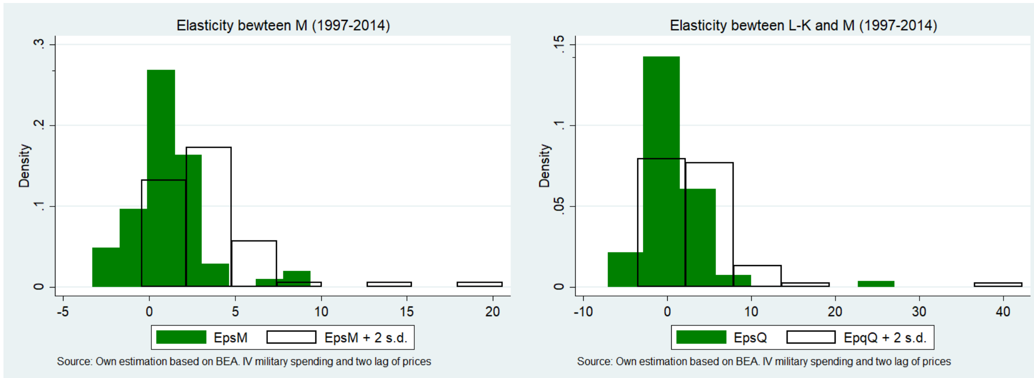

Figure 1
Distribution of IV estimates 1997-2014

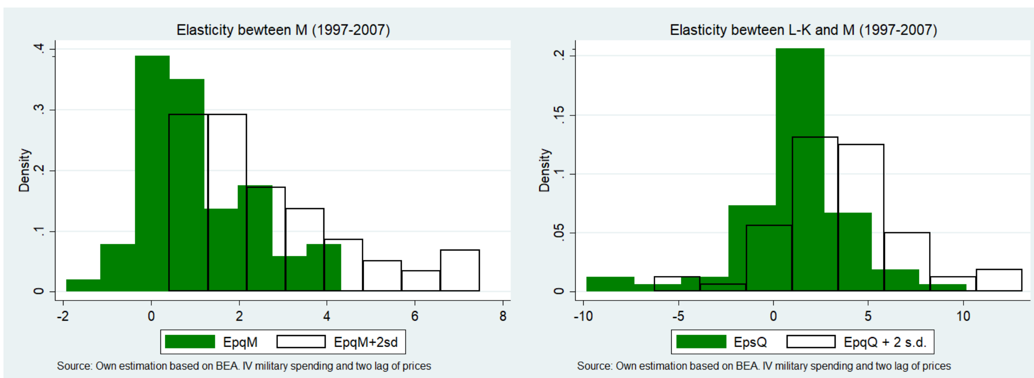

Figure 2
Distribution of IV estimates 1997-2007

3.1.4 Grouped elasticities

We now study the relationship between our estimated elasticities and sectoral spreads and firm-level outcomes (revenue and working capital). One issue is that our elasticities are generated regressors. Therefore, to improve the precision of our estimated elasticities, we aggregate sectors into 30 groups and re-estimate the sectoral elasticities. We aggregate sectors based on the ranking of sectoral elasticities in Figure 2. While grouping is important for the precision of our estimates, the same results hold without grouping, albeit with less precision (details can be found in Appendix E).

After grouping, we observe 3 sectors with negative estimates for ϵ_Q at the 95 percent confidence level: the plastic and rubber product sector (sector 26), the food and beverage stores sector (sector 29), and general merchandising stores sector (sector 30). We suspect these negative estimates are a result of small sample bias, as economic theory clearly dictates that elasticities are non-negative. Indeed, when we group these three sectors together we find that the estimated elasticity is $\epsilon_Q = -0.01$ (confidence interval $\epsilon_Q \in [-0.83, 0.77]$). For the few sectors with negative point estimates we set ϵ_Q equal to 1/1000.[14]

Table 3.2 reports the descriptive statistics of our IV elasticity point estimates, using the restricted sample. The main takeaways are that: i) service sectors have higher flexibility than manufacturing and primary sectors, in terms of both ϵ_Q and ϵ_M; ii) flexibility between labor and intermediates (ϵ_Q) is higher than the flexibility between intermediates (ϵ_M); and iii) consistent with previous studies, Atalay (2017) and Boehm et al. (2018), manufacturing and primary sectors have very low flexibility in substituting between intermediate types (ϵ_M).

Table 3.2
Grouped IV 1997-2007 point estimates

	mean	sd	p25	p75	min	max	N
ϵ_Q all	2.05	1.75	0.75	2.96	0.001	6.25	30
ϵ_Q services	2.34	1.96	0.42	3.21	0.001	6.25	19
ϵ_Q manufacturing	1.64	1.37	0.75	2.11	0.001	4.46	9
ϵ_Q primary	1.17	0.39	0.89	1.45	0.89	1.45	2
ϵ_M all	1.05	0.96	0.10	1.57	0.001	3.65	30
ϵ_M services	1.56	0.84	1.10	1.91	0.001	3.65	19
ϵ_M manufacturing	0.20	0.22	0.005	0.38	0.001	0.62	9
ϵ_M primary	0.001	—	0.01	0.001	0.001	0.001	2

Note: Own calculation using BEA sectoral data and instrumental variables.

In this section we have documented that the assumptions of common unitary elasticities across sectors ($\epsilon_Q = \epsilon_M = 1$) (Bigio and La'O (2016)) and common $\epsilon_Q \leq 1$ and $\epsilon_M < 1$ across sectors (Atalay (2017), Baqaee and Farhi (2017a), and Baqaee and Farhi (2017b)) omit important heterogeneity in production flexibility across sectors. In the next section, we take advantage of sectoral heterogeneity in technologies and study the connection between sectoral flexibility in production and the severity of sectoral financing constraints, as measured by the spreads on corporate bonds. We then use firm-level data to study whether different flexibility in production matters—is flexibility associated with firm-level performance during the Great Recession? And if so, in what way?

[14]This strategy is similar to the approach taken by Atalay (2017), who aggregates sectors to match the KLEMS database's industry classification. Then, by assuming common sectoral elasticities, the Atalay (2017) estimates $\epsilon_M \approx -0.1$. When calibrating his model, he sets $\epsilon_M = 1/10$.

4 Flexibility and spreads in US data

In this section, we study the relationship between sectoral elasticities and a measure of the degree of financial frictions: the spread on corporate bonds over Treasury bills (corrected for duration) constructed by Gilchrist and Zakrajsek (2012).[15] We complement our sectoral findings using COMPUSTAT firm-level data. We study whether firms with different production flexibility generated different revenues and working capital—as measured by current assets minus current liabilities—during the Great Recession.

We restrict our sample to the period 2002q1-2015q4. Our sectoral classification is at the 3-digit NAICS. To control for other firm-level covariates—unconnected to the elasticity—that might cause a firm or sector to pay a higher premium at a given point in time, we use COMPUSTAT data on sectoral sales, the value of tangible assets, the value of property and plants, inventories, leverage (total debt divided by assets or sales), and working capital as a fraction of sales.

Given that sectoral elasticities are assumed to be constant over time, our identification relies on interacting the elasticities with time-varying variables. In this case, we are interested in how sectoral spreads differ in recessions for firms with different elasticities of substitution, so we interact the elasticities with the Great Recession dummy, which equals one for the period 2007q4-2009q2 and zero otherwise. We also interact sectoral elasticity with sectoral debt to sales ratio to investigate whether flexibility has a differential effect on spreads depending on how leveraged are firms. Our empirical specification is

$$r_{jt} = \alpha_j + \beta_1 D_R + \beta_2 L_{jt} + \beta_3 \hat{\epsilon}_{Q_j} D_{Rt} + \beta_4 \hat{\epsilon}_{M_j} D_{Rt} + \beta_5 \hat{\epsilon}_{Q_j} L_{jt} + \beta_6 \hat{\epsilon}_{M_j} L_{jt} + \gamma X_{jt} + \nu_{jt}, \quad (8)$$

where r_{jt} is log of the median credit spread for sector j in quarter t, D_{Rt} is a recession dummy, L_{jt} is the log of leverage measured by total debt divided by sales, and X_{jt} is the vector of controls mentioned above.

All our specifications include time (year-quarter) and sector fixed effects. The $\hat{\epsilon}_{Q_j}$ and $\hat{\epsilon}_{M_j}$ terms correspond to our elasticity point estimates. Our benchmark set of results uses the IV 1997-2007 grouped elasticity estimates. In Appendix E, we report the results of using the panel FE 1997-2007 and the IV 1997-2014 methods instead.

To overcome the generated regressor problem, we evaluate the statistical significance of our estimates using a bootstrap. In the first stage, we draw M sectoral elasticities from

[15] The firm-level spread measure constructed by Gilchrist and Zakrajsek (2012) contains information about both aggregate credit conditions and firm-level default risk. Either source should deliver an upward sloping interest rate schedule – tighter conditions lead to larger spreads.

the asymptotic distribution implied by regression (7).[16] In the second stage, we use the M elasticity estimates to estimate Equation (8) M times. Each time, we save the robust standard errors of our coefficients. Our bootstrap standard error is the median of the M robust standard errors in our second stage. Alternatively, we report the bootstrap confidence interval of our M estimates of β in the second stage. Confidence intervals in bold brackets indicate that the bootstrapped estimates preserve the sign of the median estimate with a 95% level of confidence.

The results of estimating Equation (8) are reported in Table 4.1.[17] We observe a negative correlation between sectoral spreads and ϵ_Q during the Great Recession. This result holds for all sectors in column 1 and for the subgroup of sectors that excludes FIRE industries in column 4. The results in column 4, which excludes FIRE sectors, are especially strong in terms of economic and statistical significance. During the Great Recession, a 10 percent increase in the elasticity is associated with a 0.35 percent decrease in the spread. This result is statistically significant at the 99 percent confidence level. The coefficient of the interaction between ϵ_Q and leverage in column 4 is also negative and statistically significant at the 99 percent confidence level. A 10 percent increase in the elasticity, evaluated at the average value of debt to sales (2.39), is associated with a 0.7 percent decline in spreads. Considering both coefficients, a sector in the 75th percentile of ϵ_Q ($\epsilon_Q = 2.96$) paid a bond spread 220 basis points (2.2 percentage points) lower than a sector in the 25th percentile of ϵ_Q ($\epsilon_Q = 0.75$).

[16] If the elasticity draw lies below zero, we set it to be 1/1000.

[17] We did not observe any statistically-significant relationship between ϵ_M and spreads. Therefore, to simplify exposition, we do not report the coefficients for ϵ_M.

Table 4.1
Sectoral elasticities and GZ spreads

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) All	(5) Manufacturing	(6) Service
DR	0.67***	0.43***	0.68***	0.65***	0.49***	0.65***
	(0.067)	(0.105)	(0.093)	(0.068)	(0.109)	(0.096)
ln (D/sales)	0.39***	0.50***	0.37***	0.43***	0.56***	0.40***
	(0.040)	(0.096)	(0.050)	(0.041)	(0.098)	(0.051)
$\ln \epsilon_Q \cdot D_R$	-0.029*	-0.017	0.116	-0.035***	-0.027	0.139
	(0.016)	(0.022)	(0.114)	(0.012)	(0.021)	(0.123)
	[-0.099,-0.013]	**[-0.116,-0.015]**	**[0.002,0.165]**	**[-0.115,-0.011]**	**[-0.167,-0.026]**	**[0.017,0.201]**
$\ln \epsilon_Q \cdot \ln(D/sales)$	-0.040	-0.108*	0.177***	-0.081***	-0.143***	0.204
	(0.033)	(0.054)	(0.023)	(0.029)	(0.051)	(0.144)
	[-0.138,-0.007]	**[-0.358,-0.068]**	**[0.047,0.0261]**	**[-0.246,-0.019]**	**[-0.469,-0.101]**	**[0.050,0.327]**
Observations	2,493	989	1,376	2,356	933	1,295
R-squared	0.623	0.653	0.645	0.619	0.657	0.639
Number of sector	53	18	32	50	17	30
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimated coefficients of a regression between sectoral bond spreads as dependent variable and a Great Recession dummy, sectoral debt to sales ratio, and the interaction between the previous controls and the IV 1997-2007 sectoral elasticities $\epsilon_{\hat{Q}_j}$. We also control for time fixed-effects, sector fixed-effects, value of tangible assets, the value of property and plants, inventories, and working capital as a fraction of sales. For the elasticity coefficients, we report the median bootstrap estimate and the median robust standard error (in parentheses). We also report the 5%-95% bootstrap confidence interval of the coefficients. Columns 4-6 excludes FIRE and Petroleum sectors

We also split the sample between manufacturing and service sectors. These industries are heterogeneous along many dimensions relevant for our study. Service sector firms are generally more leveraged, use intermediate inputs less intensively, display higher production flexibility, and paid higher average spreads during the Great Recession (see Tables 7.5-7.6 in Appendix B). The results in columns 2-3 and columns 5-6 illustrate interesting heterogeneity within these industries. The results for manufacturing industries mimic the aggregated results. However, we observe that within service sectors, higher production flexibility is associated with higher bond spreads. The statistical significance of these results is mixed when we use the bootstrap implied t-statistics. However, once we consider the bootstrap confidence interval, the estimated coefficients for manufacturing firms are negative at the 95% of confidence, while the estimated coefficients for services are positive.

In Appendix E, Tables 7.8-7.11, we show that our results do not depend on whether we group our sectors, whether we use alternative—although more biased—estimated elasticities (IV 1997-2014 and FE 1997-2007), whether we define leverage as debt to sales or debt to assets, whether we bootstrap or not, and whether, instead of bootstrapping we adjust our elasticities by statistical significance. The estimated relationship between spreads and elasticities is stronger—that is, we get larger point estimates—using our IV elasticities (compare Table 4.1 to Table 7.9). This stronger relationship is a consequence of the fact that OLS underestimates sectoral heterogeneity.

4.1 Flexibility and firm-level performance

We complement our previous findings using firm level data from COMPUSTAT. We provide evidence that high flexibility in production is associated with higher operational revenues and higher working capital. Consistent with the previous evidence, within manufacturing firms flexibility improves firm-level performance, while within service sector firms flexibility, if anything, is associated with poor firm-level performance. We run the regression

$$y_{it} = \alpha_i + \gamma_1 D_{Rt} + \gamma_2 L_{it} + \gamma_3 \hat{\epsilon}_{Q_j} D_{Rt} + \gamma_4 \hat{\epsilon}_{Q_j} L_{it} + \phi X_{it} + \nu_{it}, \tag{9}$$

where y_{it} is either the log of firm level revenue or working capital. X_{it} represents firm level controls, in this case the value of inventories. We also include firm level and year-quarter fixed-effects. Table 4.2 presents the relationship between firm revenue and flexibility. In column 1, we observe a positive relationship between $\hat{\epsilon}_{Q_j} D_{Rt}$ and $\hat{\epsilon}_{Q_j} L_{it}$ and revenue. The relationship is statistically significant and implies that a 10 percent increase in the elasticity is associated with a 0.1 percent increase in operational revenues during the Great Recession. A sector in the 75th percentile of ϵ_Q ($\epsilon_Q = 2.96$) generated an additional 14 U.S million dollars in quarterly revenue relative to a sector in the 25th percentile of ϵ_Q ($\epsilon_Q = 0.75$). If we split the sample, we observe similar results within manufacturing firms. While the evidence within service sector firms is also consistent with the results in the previous section, the coefficients are not statistically different from zero.

Table 4.2
Firms' revenue and flexibility (excludes FIRE sector firms)

VARIABLES	(1) All	(2) Manufacturing	(3) Service
DR	0.372***	0.206***	0.378***
	(0.047)	(0.043)	(0.060)
ln (D/sales)	0.0098**	-0.0002	0.0139**
	(0.004)	(0.002)	(0.0062)
$\ln \epsilon_Q \cdot D_R$	0.007***	0.0015	0.0156
	(0.003)	(0.0026)	(0.022)
	[**0.004,0.034**]	[**0.0014,0.0056**]	[-0.0054, 0.028]
$\ln \epsilon_Q \cdot \ln(D/sales)$	0.0023*	0.0026*	-0.0002
	(0.0013)	(0.0014)	(0.012)
	[**0.0022,0.010**]	[**0.0025, 0.0125**]	[-0.0032,0.0026]
Observations	196,702	86,161	93,983
R-squared	0.284	0.382	0.247
Number of firm	9,137	3,896	4,328
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Note: This table reports the estimated coefficients of a regression between firm-level sales as dependent variable and a Great Recession dummy, sectoral debt to sales ratio, and the interaction between the previous controls and the IV 1997-2007 sectoral elasticities $\epsilon_{\hat{Q}_j}$. We also control for time fixed-effects, firm fixed-effects, and value of inventories. For the elasticity coefficients, we report the median bootstrap estimate and the median robust standard error (in parentheses). We also report the 5%-95% bootstrap confidence interval of the coefficients.

We now study the relationship between flexibility and working capital, which we regard as a measure of short-term liquidity. The evidence in Table 4.3 suggests a strong positive relationship between flexibility and working capital. A 10% increase in flexibility is associated with a 0.16% in working capital. A sector in the 75th percentile of ϵ_Q ($\epsilon_Q = 2.96$) displayed 7.7 U.S million dollars more quarterly working capital than a sector in the 25th percentile of ϵ_Q ($\epsilon_Q = 0.75$).[18]

Table 4.3
Firms' working capital and flexibility (excludes FIRE sector firms)

VARIABLES	(1) All	(2) Manufacturing	(3) Service
DR	0.374***	0.240**	0.405***
	(0.061)	(0.074)	(0.0717
ln (D/sales)	-0.107***	-0.116***	-0.095***
	(0.006)	(0.006)	(0.012)
$\ln \epsilon_Q \cdot D_R$	0.0125***	0.0096***	0.0247
	(0.0036)	(0.0039)	(0.055)
	[**0.0096,0.0591**]	[**0.0093,0.0462**]	[-0.0085, 0.0363]
$\ln \epsilon_Q \cdot \ln(D/sales)$	0.0038**	0.0043***	0.0171
	(0.0017)	(0.0018)	(0.023)
	[**0.0035,0.0183**]	[**0.0042, 0.0221**]	[**0.0039,0.0225**]
Observations	196,702	86,161	93,983
R-squared	0.284	0.382	0.247
Number of firm	9,137	3,896	4,328
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Note: This table reports the estimated coefficients of a regression of firm-level sales on a Great Recession dummy, sectoral debt to sales ratio, and the interaction between the previous controls and the IV 1997-2007 sectoral elasticities $\epsilon_{\hat{Q}_j}$. We also control for time fixed-effects, firm fixed-effects, and value of inventories. For the elasticity coefficients, we report the median bootstrap estimate and the median robust standard error (in parentheses). We also report the 5%-95% bootstrap confidence interval of the coefficients.

Consistent with our previous results, the connection between flexibility and firm-level performance is preserved within manufacturing firms but not for service sector firms. In Appendix E, we show that our results also hold if we use our less precise IV elasticity estimates over the entire sample. Similar results also hold if we use the panel fixed-effect elasticities for the period 1997-2007. In both of these cases we do not group elasticities, which also shows that our results also do not depend on this choice.

[18]The average working capital of firms in the sample is $170 million in 2009 quarter 1.

5 Understanding the role of flexibility

In this section, we develop a simple model that can explain our facts. Compared to Bigio and La'O (2016) and Baqaee and Farhi (2017a), who also study multisector models with linkages and frictions, our framework allows for heterogeneity in sectoral elasticities and frictions.

5.1 A simple model

There are two sectors—the first sector produces using only labor, and the second sector produces using labor and intermediates from both sectors:

$$Q_1 = Z_1 L_1$$
$$Q_2 = Z_2 \left(a_2^{\frac{1}{\epsilon_Q}} L_2^{\frac{\epsilon_Q - 1}{\epsilon_Q}} + (1 - a_2)^{\frac{1}{\epsilon_Q}} M_{12}^{\frac{\epsilon_Q - 1}{\epsilon_Q}} \right)^{\frac{\epsilon_Q}{\epsilon_Q - 1}}.$$

Each sector faces a collateral constraint on working capital:

$$\theta_1^w w L_1 \leq \eta_1 P_1 Q_1 \tag{10}$$
$$\theta_2^w w L_2 + \theta_{12}^m P_1 M_{12} \leq \eta_2 P_2 Q_2. \tag{11}$$

Firms in sector j need to externally finance a fraction θ_j^w of the wage bill wL_j, and a fraction θ_{ij}^m of the cost of intermediates purchased from sector i $P_i M_{ij}$. However, firms are limited in the amount of borrowing they can obtain. Different sectors can pledge a different fraction η_j of total sales as collateral. The variable μ_j denotes the Lagrange multiplier for the sectoral borrowing constraint in Equation (10), which represents the firms' shadow cost of debt—that is, μ_j represents how much firms in sector j value a marginal increase in external funds that would allow them to produce closer to the optimal scale.[19]

The representative household maximizes

$$U(C) = \log C$$

subject to the budget constraint

$$w\bar{L} \geq P_2 C;$$

labor supply is inelastic, which is not essential but simplifies the algebra.

[19] See Footnote 5 for a discussion of this constraint.

In equilibrium, labor market clearing requires

$$\bar{L} = L_1 + L_2,$$

and goods market clearing requires

$$\begin{aligned} M_{12} &= Q_1 \\ C &= Q_2. \end{aligned}$$

Note that, for simplicity of the resulting algebra, the output of sector one is not consumed. Adding capital – as a fixed input or rented input – would not change our results if value added is produced using a Cobb-Douglas aggregate of capital and labor, so again for ease of presentation we simply ignore it. We normalize both wages w and total labor endowment $\bar{L}$ to 1.

We vary the values of the elasticities and examine the relationship between the Lagrange multiplier μ_2 on the collateral constraint for sector 2 and the elasticity of interest. If we were to assume that sectoral production functions were Cobb-Douglas (as in Bigio and La'O (2016)) and constant returns to scale, then sectors would either be constrained or unconstrained; for example, a sector would be constrained if $\eta_2 < 1$ and $\theta_j^w + \sum \theta_{ij}^m = 1$ since the left-hand-side of the collateral constraint equals revenue at the unconstrained profit-maximizing point. To deal with this problem while maintaining Cobb-Douglas production functions, Bigio and La'O (2016) assume sector-specific decreasing returns to scale; however, their strategy for identifying the decreasing returns to scale parameter is indirect, as opposed to our direct measurement of the elasticities.

5.2 Flexibility and frictions

We now proceed to examine two predictions from our model: (i) the extent a constrained sector is constrained (intensive) and (ii) the frequency a given sector is constrained (extensive) ; these moments correspond to the quantitative size of μ_j if $\mu_j > 0$ and to the frequency with which $\mu_j > 0$. The model identifies four quantities that matter for these implications: 1) the importance of intermediates in production $(1 - a_2)$; 2) the borrowing capacity of a sector (η); 3) the fraction of labor or intermediates costs that must be paid in advance (θ_2^w or θ_{12}^m); and 4) whether $\epsilon_Q > 1$ or $\epsilon_Q < 1$.

The next proposition describes the intensive margin of sectoral frictions. If sectors are constrained, we show that the model can deliver the negative correlation between elasticities and spreads observed in the data as well as the heterogeneous results for service and manufacturing sectors.

Proposition 1 *Suppose sectors 1 and 2 are constrained ($\mu_1 > 0$ and $\mu_2 > 0$). Then, if sector 2 only needs to externally finance intermediate input expenses ($\theta_{12}^m = 1$ and $\theta_2^w = 0$), we have*

- *A higher elasticity ϵ_Q in sector 2 relaxes (tightens) the constraint, $\frac{\partial \mu_2}{\partial \epsilon_Q} < 0$ (> 0), if the friction adjusted relative cost of intermediates is high (low), $\frac{\phi_m}{Z_1} > 1$ (<1), where*

$$\phi_m = \frac{(1-\eta_1\eta_2)(1-a_2)}{\eta_1\eta_2 a_2}.$$

Also, if sector 2 only needs to externally finance the labor input ($\theta_{12}^m = 0$ and $\theta_2^w = 1$), we have

- *A higher elasticity ϵ_Q relaxes (tightens) the constraint, $\frac{\partial \mu_2}{\partial \epsilon_Q} < 0$ (> 0), if the friction adjusted relative cost of labor is high (low), $Z_1\phi_w > 1$ (< 1), where*

$$\phi_w = \frac{(1-\eta_2)\, a_2}{(1-a_2)\, \eta_2}.$$

Proof: see Appendix A.

Given that $w = 1$, the terms $\frac{\phi_m}{Z_1}$ and $Z_1\phi_w$ can be interpreted as the friction-adjusted relative prices of intermediates and labor, respectively. The intuition behind Proposition 1 goes as follows. When the friction adjusted cost of the constrained input is high, there is a premium for production flexibility. More flexible firms are able to dampen the effect of the constraint by using more of the unconstrained input. Low flexibility firms must keep using the more expensive input, which then tights the credit constraint even further. On the other hand, when the constrained input has a low friction-adjusted relative price, more flexible firms want to use more of the constrained input, which is not possible due to the binding constraint.

First, we explain how the model replicates the negative relationship between spreads and ϵ_Q in columns 1 and 4 of Table 3.3. The model can deliver the negative relationship between ϵ_Q and μ_2 if i) frictions affect mostly intermediates and the friction-adjusted relative price of intermediates ($\frac{\phi_m}{Z_1}$) is high or ii) frictions affect mostly labor and the friction-adjusted relative price of labor ($Z_1\phi_w$) is high.

To infer the friction-adjusted relative price of inputs, we need information on two unobservables, productivity (Z) and the collateral constraint parameters η, and one observable, the importance of labor in production (a). The average value of a in the data is smaller than 0.5 (see Table 7.1). Therefore, given a value of the unobservables (Z,η), ϕ_m tends to be larger than one and ϕ_w tends to be smaller than one. If in addition, we assume that the collateral constraint parameters were relatively low during the Great Recession, it is more likely that $\phi_m > 1$ and $\phi_w < 1$. Hence, using our model to interpret the facts in section 2 implies that working capital constraints in the use of intermediates played an important role during the Great Recession.

The model also offers insights on the heterogeneity we observe between manufacturing and service sectors. Within manufacturing sectors, we observe an inverse relationship between ϵ_Q and frictions, whereas for service sectors we observe a positive relationship. Manufacturing and services are heterogeneous in their input intensity: in Table 7.1 we see that service sectors are labor-capital intensive (high a), while manufacturing sectors are intermediate input intensive (low a). Thus, for low η_2 we have $\phi_m > 1$ and $\phi_w < 1$, which rationalizes our facts if manufacturing and services are both constrained in the use of intermediates.

The next proposition describes the extensive margin of constraints: what is the likelihood of a sector becoming constrained? Here, we highlight another dimension of sectoral heterogeneity that matters: whether labor and intermediates are complementary ($\epsilon_Q < 1$) or substitute inputs ($\epsilon_Q > 1$). We focus on cases with countercyclical frictions; that is, constraints become binding after negative productivity (or financial) shocks. The next proposition focuses on productivity shocks to the upstream sector. In Appendix A, we present results for financial shocks to the upstream sector.

Proposition 2 *Let* Z_1^* *denote the threshold productivity in sector* 1 *that results in sector* 2 *being constrained. Then, if sector 2 only needs to externally finance the intermediates* ($\theta_{12}^m = 1$ *and* $\theta_2^w = 0$)*, we have*

- *If labor and intermediates are complementary inputs* ($\epsilon_Q < 1$) *leverage and the Lagrange multiplier of sector 2 are countercyclical when* $\phi_m < 1$*, and a higher elasticity* ϵ_Q *reduces the likelihood of sector 2 becoming constrained,* $\frac{\partial Z_1^*}{\partial \epsilon_Q} < 0$*,*

Also, if sector 2 only needs to finance the labor input ($\theta_{12}^m = 0$ *and* $\theta_2^w = 1$)*, we have*

- *If labor and intermediates are substitute inputs* ($\epsilon_Q > 1$)*, leverage and the Lagrange multiplier are countercyclical when* $\frac{\eta_2 \phi_w}{\eta_1 + \eta_2 - 1} < 1$*, and a higher elasticity* ϵ_Q *increases the likelihood of sector 2 becoming constrained,* $\frac{\partial Z_1^*}{\partial \epsilon_Q} > 0$.

Proof: see Appendix A.

Proposition 2 shows that within the group of low flexibility sectors $\epsilon_Q < 1$, if the constraint affects intermediates, then increases in the relative price of intermediates (lower Z_1) increase working capital needs more than revenues, implying a higher probability of hitting the constraint. Within the group of high flexibility sectors ($\epsilon_Q > 1$), if the constraint affects labor, the increase in the relative cost of intermediates increases labor demand. Therefore, in this case, higher flexibility increases the likelihood of hitting the constraint. Figures 7 and 8 in Appendix C illustrate this mechanism for different parameterizations.

This proposition can also rationalize the heterogeneity between manufacturing and services. While not all manufacturing sectors have $\epsilon_Q < 1$ and not all service sectors have $\epsilon_Q > 1$, on average, service sectors have higher flexibility than manufacturing sectors. Proposition 2 characterizes times where constraints are not binding, which is typically when η and/or Z are high. In such cases, using the observed values of a in the formulas of ϕ_m and ϕ_w, it is reasonable to expect that for high values of η and/or Z we would observe $\phi_m < 1$ and $\frac{\eta_2 \phi_w}{\eta_1 + \eta_2 - 1} < 1$.

In summary, the model predicts that in an environment with increasing intermediate input costs (as suggested by Figures 9 and 10 in Appendix C), lower flexibility sectors—within the group of low elasticity sectors ($\epsilon_Q < 1$)—increase their borrowing needs and are therefore more likely to hit a constraint in the use of intermediates. On the other hand, higher flexibility sectors—within the group of high elasticity sectors $\epsilon_Q > 1$—increase their borrowing needs and are therefore more likely to hit a constraint in the use of labor.

6 Macroeconomic implications

In this section, we investigate the macroeconomic implications of our generalized model. We proxy sectoral distortions with credit spreads and use our estimated sectoral elasticities. Our goal is to reevaluate the role of of sectoral distortions and input-output connections in amplifying the Great Recession. As a side product, we identify those sectors most responsible for this amplification.

6.1 The role of sectoral heterogeneity in the Great Recession

We generalize our model to 66 sectors and assume that the household consumes a fraction β_j of final goods from sector j (see Miranda-Pinto (2018a)). The representative household utility function is $U(C,L) = \log C - L$. The sectoral production functions and working capital constraints are given by Equations 1-3. Firms maximize profits subject to 1-3. We assume that any profits (obtained due to binding collateral constraints) are thrown into the ocean (or given by absentee owners who play no other role).

The model features occasionally-binding working capital constraints (as we discussed earlier). However, given that our main purpose is to investigate the Great Recession, we assume that sectoral constraints are binding; we solve the model for a given set of sectoral wedges. Given the wedges, we can obtain solutions for sectoral prices and aggregate GDP (see Miranda-Pinto (2018a) online Appendix for more details).

To keep things simpler, we assume that $\epsilon_{M_j} = \epsilon_{Q_j}$ for all j.[20] Real GDP equals aggregate consumption C and is given by

$$\log C_t = \beta' \log c_t = -\beta' \log P_t + \beta' \log \beta,$$

where, for a given set of wedges ϑ, the vector of sectoral prices is

$$\log P_t = \frac{1}{1-\epsilon_Q} \log\left(\left[I - Z_t^{\epsilon_Q - 1} \circ \vartheta_t^{\epsilon_Q - 1} \circ \left((1-a) \circ \Omega' \right) \right]^{-1} \left(Z_t^{\epsilon_Q - 1} \circ \vartheta_t^{\epsilon_Q - 1} \circ a \right) \right).$$

Aggregate GDP is a function of the network structure Ω, the sectoral wedges ϑ, the sectoral elasticities, and sectoral productivity. Sectoral wedges are a function of sectoral borrowing ability η and productivity Z. To focus on the role of financing frictions during the Great Re-

[20] If $\epsilon_M \neq \epsilon_Q$, there is no closed form solution to the model. While these elasticities are different for a given sector, the facts in section 2 show that service industries have higher ϵ_Q and ϵ_M. Therefore, as long as the heterogeneity in sectoral elasticities between service and non-service sectors is the meaningful dimension, our assumption still allows us to make our point.

cession, we focus on changes in borrowing capacity and omit the role of sectoral productivity shocks. Therefore, we set $Z_j = 1$ for every sector j and every period t. Given that Z plays a key role only in shaping the extensive margin of constraints (Proposition 2), which we have already shut down by assuming binding constraints, the assumption of $Z = 1$ is innocuous in this section.

Note that, as demonstrated by Bigio and La'O (2016), in models with input-output linkages and frictions, sectoral distortions reduce GDP via total factor productivity (TFP) losses (*efficiency wedge*) or via labor wedge. In this paper, due to the assumptions of constant returns to scale and that firm-level profits are thrown to the ocean, there is not labor wedge. Therefore, sectoral distortions reduce GDP only from the misallocation of inputs throughout the production network.

6.1.1 GZ spreads as a proxy for frictions

We calibrate sectoral wedges following Bigio and La'O (2016). The authors directly use sectoral bond spreads to proxy for sectoral frictions:

$$\vartheta_{jt} = \frac{1}{1 + r_{jt}},$$

where r_{jt} is the median bond spread of firms in sector j at time t. Out of the 66 non-government sectors, 10 sectors do not have spread data for every year in our sample. For these sectors, we use the cross-sectoral average bond spread to impute the missing observations. We feed the time series of sectoral distortions into the model and study the implied evolution of aggregate GDP over the period 1998-2016. We calibrate the economy to match the US 2007 input-output structure (that is, we match the input-output flows using the coefficients of the Ω matrix).

Figure 3 show that, for a given set of frictions, different degrees of (common) flexibility in production have no role in mitigating or magnifying the effect of sectoral distortions on aggregate GDP: the series for real GDP growth are almost identical with $\epsilon_Q = 1$ (in blue) and $\epsilon_Q = 2$ (in red), for all j. This result is purely due to the assumption of homogeneous flexibility across sectors. Similar (non-reported) results hold when $\epsilon_Q = 0.1$ for all sectors.

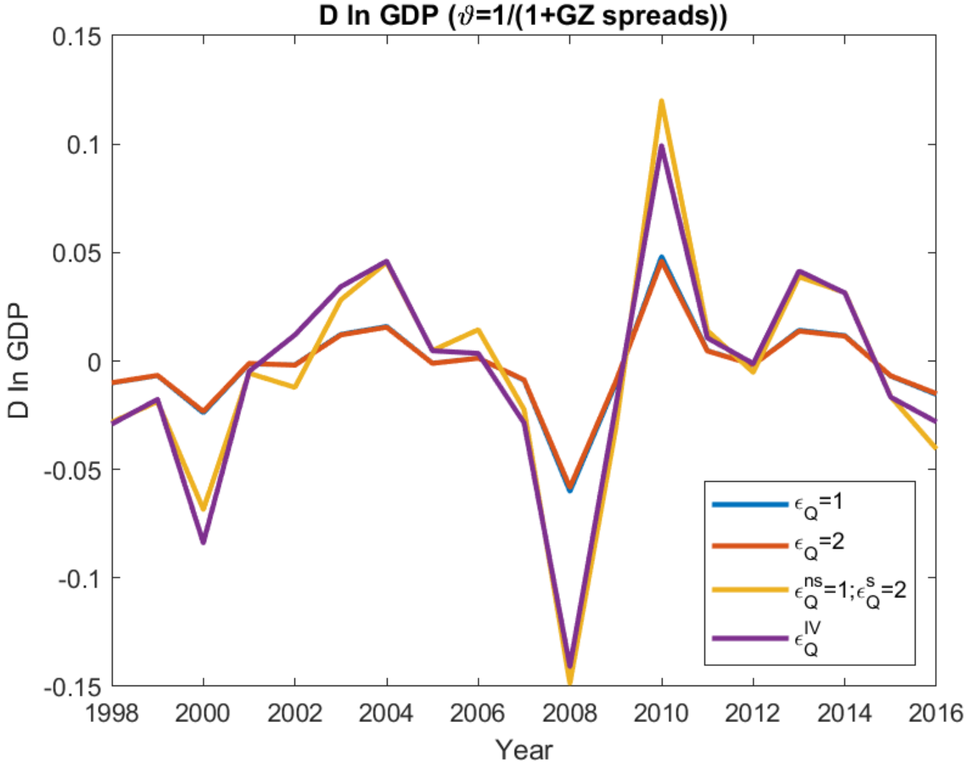

Figure 3
Aggregate effect of frictions

Once we introduce sectoral heterogeneity in elasticities, the results are completely different. If we calibrate the sectoral elasticities using our statistically-adjusted IV 1997-2007 estimates, our model implies that sectoral frictions have a much larger aggregate effect (in purple).[21] A model with heterogeneous elasticities predicts a role for credit frictions that is 2.4 times larger than the implied by homogeneous elasticities, be they unitary or not. To confirm that the meaningful heterogeneity is between service and non-service industries' flexibility, we calibrate our model assuming that non-service sectors have unitary elasticity and service sectors have an elasticity of 2 (in yellow). The model implied GDP growth is practically the same as the one implied by our estimated elasticities ϵ_Q^{IV}. To have an idea of the magnitude, accounting for sectoral heterogeneity in elasticities has a quantitative effect that is greater or equal than the amplification effect of input-output linkages in Bigio and La'O (2016).[22]

[21] We set $\epsilon_{Q_j} = 1$ if the estimated $\beta_j = \epsilon_{Q_j} - 1$ is not statistically different from zero.

[22] Note that unlike Bigio and La'O (2016), we do not drop FIRE sectors from the input-output matrix. However, we checked that our results are not driven by the FIRE sectors having unusual elasticities. If we

6.1.2 The role of sectoral linkages

We also study the role of input-output linkages in the amplification of financial shocks. We compare our benchmark calibrated economy—both with homogeneous and heterogeneous elasticities—to a horizontal economy in which firms in a given sector use intermediate inputs only from firms in the same sector. We use the same calibrated vector of a in both cases, but the key difference is in Ω. The benchmark economy uses the observed intermediate input shares in the data, while the economy without linkages assumes that Ω is the identity matrix.

We observe that input-output linkages play a key role in amplifying sectoral constraints. Compared to the economy with intermediate inputs but without linkages (Figure 4, blue line), the economy with input-output linkages (Figure 4, red line) displays a much sharper downturn in 2008 (2.3 times larger). Indeed, from comparing Figure 4 to Figure 3, we infer that most of the input misallocation in our economy arises from input-output connections amplifying sectoral distortions.

change the FIRE sectors elasticities to be unitary, Figure 3 is practically unchanged.

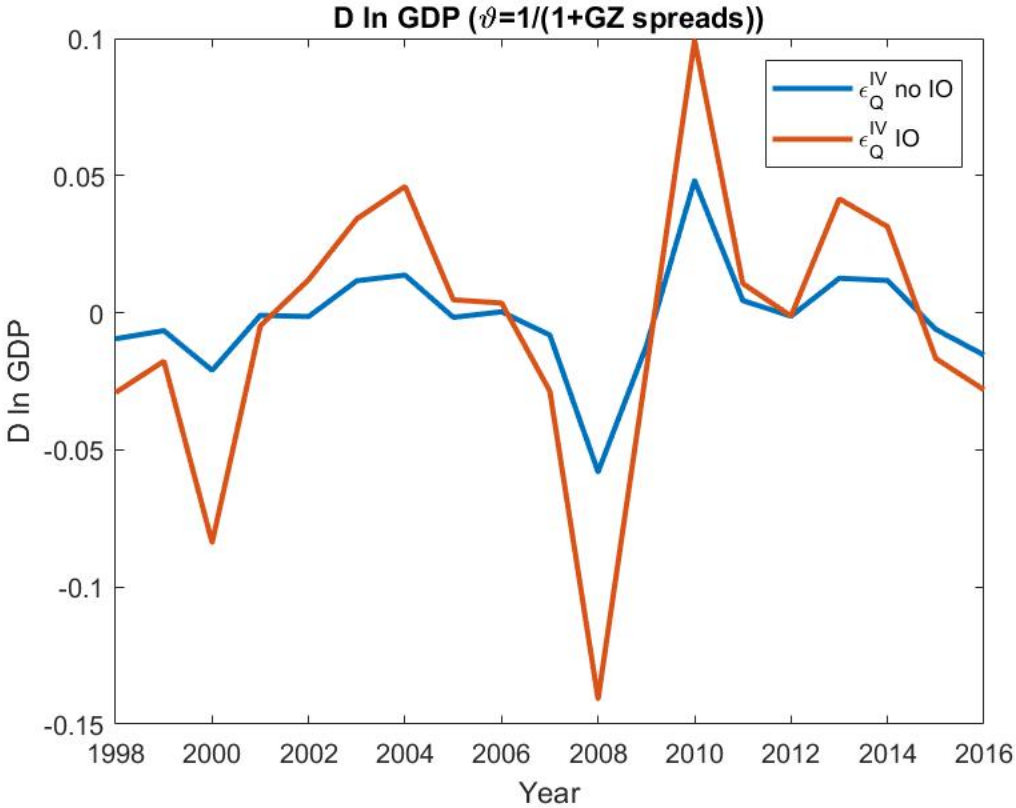

Figure 4
Network amplification with heterogeneous elasticities

Interestingly, input-output connections do not amplify input misallocation if the production elasticities are homogeneous. Figure 4 shows that the downturn in 2008 is only 1.01 times larger when elasticities are common across sectors, whether they are unitary or substantially smaller than one (0.4). Therefore, the large misallocation of inputs in our model is caused by two sources of heterogeneity: i) the heterogeneity in sectoral elasticities; and ii) the heterogeneity in input-output connections.

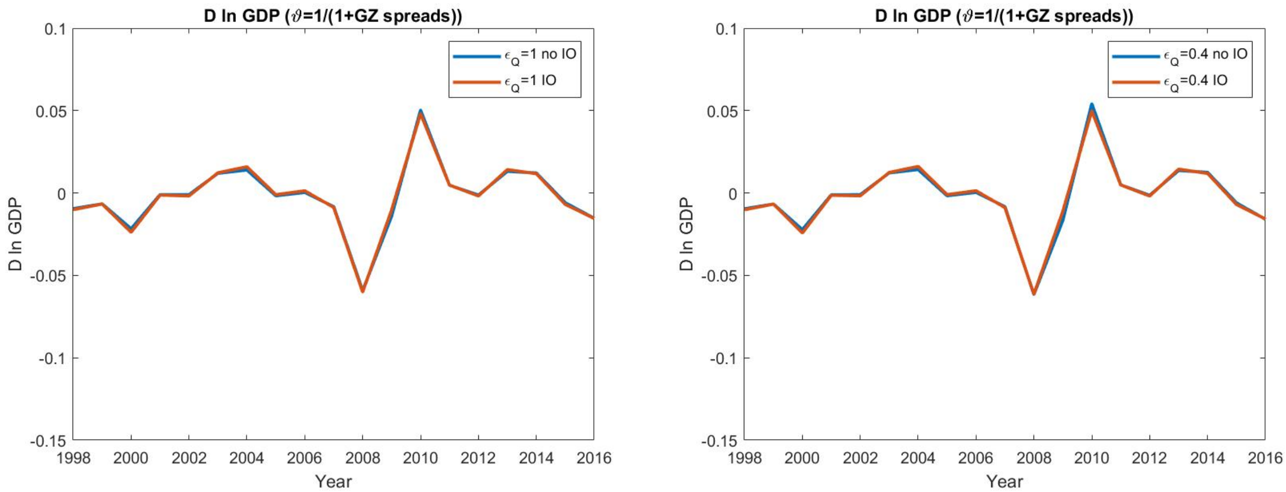

Figure 5
Network amplification with homogeneous elasticities

6.2 Flexibility and sectoral centrality

We now investigate a mechanism that may lie behind the results in Figures 3 and 4. To this end, we ask which industries are responsible for the large implied downturn observed if the elasticities are heterogeneous. We start by assuming that all industries have unitary elasticities. We then select the sectors with $\epsilon_Q > 1$ and one by one investigate the macroeconomic effect of increasing ϵ_Q from 1 to the actual estimated value. Our quantitative exercise leads us to conclude that the sectors "other real estate", "management of companies and enterprises", and "administrative and support services" account for most of the macroeconomic effect of sectoral distortions.

Figure 6 (yellow line) plots the results assuming that all industries have $\epsilon_Q = 1$, except the for these three sectors which have their estimated elasticities ($\epsilon_Q \in [2.2,5.5]$). We can see that the downturn here is nearly the same size as the one with the full span of heterogeneous elasticities.

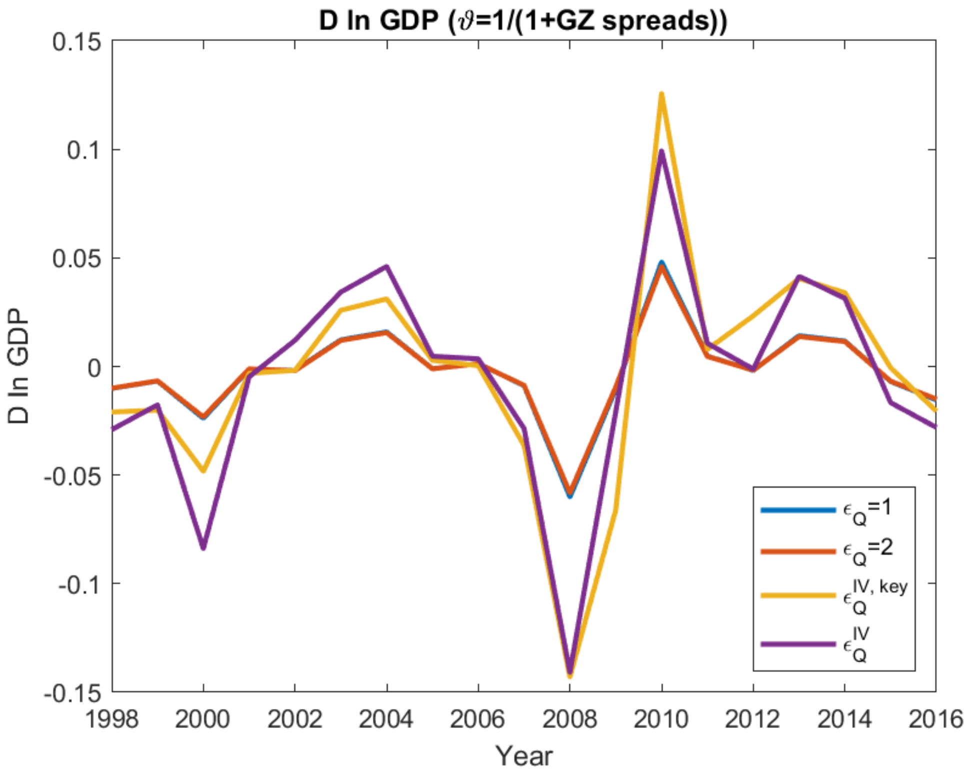

Figure 6
Aggregate effect of frictions: key sectors

What is special about these industries besides the fact that they display high production flexibility? These sectors turn out to be key intermediate input suppliers. Figure 11 plots the U.S input-output matrix in 2007. Bright rows indicate industries are important suppliers of intermediates. These three industries display very bright rows: these industries alone provide 15 percent of the total intermediate inputs in the economy. Furthermore, they supply intermediates to all sectors in the economy, so their effect is both large and widespread.

In Appendix B, Table 7.7, we provide a more detailed analysis of sectoral centrality. We report the top-20 sectors in terms what is the implied downturn in 2009—compared to the Cobb-Douglas case—from increasing ϵ_Q from 1 to 2. Consistent with Figure 11, "other real estate", "management of companies and enterprises", and "administrative and support services" sectors are top-10 in terms of centrality, and, in addition, display large estimated ϵ_Q.

Two questions naturally arise. First, why do larger elasticities in these particular upstream sectors generate larger efficiency losses? And second, why this amplification does not manifest if all industries display high flexibility ($\epsilon_Q = 2$ for all j)? The reason is that during the Great Recession, due to binding constraints, these sectors are distorted and appear to have lower effective production elasticities. Therefore, in response to tightened frictions, their prices increase relatively more than what they would increase absent of frictions, which then further increases production costs—and therefore wedges—for their many less-flexible downstream sectors. These results share the intuition in Osotimehin and Popov (2017), where eliminating markups has higher TFP gains when production flexibility is higher. Nevertheless, the analysis in Osotimehin and Popov (2017) assumes homogeneous elasticities. In our case, heterogeneity in production flexibility is the key.

7 Conclusion

In this paper we have shown that the heterogeneity in sectoral production elasticities in the U.S is important to understand the amplification mechanisms behind the Great Recession. Empirically, our results indicate that during the Great Recession, firms with higher substitutability in production paid lower spreads on corporate bonds, experienced higher revenues, and held more working capital. We use this evidence to build a multisector model with heterogeneous elasticities and working capital constraints in the use of inputs.

We then study the macroeconomic implications of our model. Our results indicate that not accounting for heterogeneous elasticities leads to a significant underestimation of the role of sectoral distortions and input-output linkages in the Great Recession. We also identify real estate and professional services sectors as playing a central role in the Great Recession due to their high elasticity and centrality as a supplier of intermediates to downstream less-flexible sectors.

We believe our elasticity estimates will be useful for researchers trying to understand questions regarding the sources of business cycles (sectoral vs. aggregate) and the causes of comovement (outputs and inputs) between sectors. Moreover, our model economy—with sectoral linkages and distortions—has implications for the design of sectoral policies. Sectoral distortions can be important during macroeconomic downturns or in developing economies with underdeveloped financial sectors. The existing literature (Miranda-Pinto (2018a) and Liu (2017)) does not take into account the heterogeneity of sectoral flexibility, which we see as a natural next step.

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Appendix A: Mathematical Appendix

Model's implied regression to estimate elasticities

Let's start by defining $\rho_{Q_j} = \frac{\epsilon_{Q_j}-1}{\epsilon_{Q_j}}$. To derive the Equation (6) we solve the cost minimization problem for firms in sector j, subject to the working capital constraint in the use of value-added and intermediates $\theta_j^v P_j^v V_j + \theta_j^m P_j^M M_j \leq \eta_j P_j Q_j$. The Lagrangian of this problem is (max - (cost))

$$\begin{aligned}\mathcal{L} &= -P_j^v V_j - P_j^M M_j - \lambda^1 \left(Q_j - Z_j \left[a_j^{\frac{1}{\epsilon_{Q_j}}} L_j^{\rho_{Q_j}} + (1-a_j)^{\frac{1}{\epsilon_{Q_j}}} M_j^{\rho_{Q_j}} \right]^{\frac{1}{\rho_{Q_j}}} \right) \\ & -\mu_j^C \left(\theta_j^v P_j^v V_j + \theta_j^m P_j^M M_j - \eta_j P_j Q_j \right).\end{aligned}$$

The first-order necessary and sufficient conditions for M_j is

$$-P_j^M + \lambda^1 \frac{\partial Q_j}{\partial M_j} + \mu_j^C \eta_j P_j \frac{\partial Q_j}{\partial M_j} - \mu_j^C \theta_j^m P_j^M = 0.$$

Rearranging, using the fact that $\frac{\partial Q_j}{\partial M_j} = Z_j^{\rho_{Q_j}} \left(\frac{a_j Q_j}{M_j} \right)^{\frac{1}{\epsilon_{Q_j}}}$ and that in competitive markets the marginal cost of production in sector j (λ^1) is the price of good P_j, we have

$$P_j^M = Z_j^{\rho_{Q_j}} \left(\frac{a_j Q_j}{M_j} \right)^{\frac{1}{\epsilon_{Q_j}}} P_j \frac{\left(1 + \mu_j^C \eta_j\right)}{\left(1 + \mu_j^C \theta_j^m\right)}. \tag{12}$$

Let $\overline{\mu}_j = \frac{1+\mu_j^C \eta_j}{1+\mu_j^C \theta_j^m}$. Raising the previous equation to the power of ϵ_{Q_j}, taking logs, and rearranging we obtain

$$\log \left(\frac{P_{jt}^M M_{jt}}{P_{jt} Q_{jt}} \right) = \log(a_j) + (1-\epsilon_{Q_j}) \log \left(\frac{P_{jt}^M}{P_{jt}} \right) + (\epsilon_{Q_j} - 1) \log Z_{jt} + \epsilon_{Q_j} \log \overline{\mu}_{jt}. \tag{13}$$

Now, we minimize the cost of the intermediate input bundle $\sum_{i=1}^N P_i M_{ij}$ subject to $M_j = \left(\sum_{i=1}^N \omega_{ij}^{\frac{1}{\epsilon_{M_j}}} M_{ij}^{\rho_{M_j}} \right)^{\frac{1}{\rho_{M_j}}}$. The Lagrangian for this problem is

$$\mathcal{L} = -\sum_{i=1}^{N} P_i M_{ij} - \lambda^2 \left(M_j - \Big(\sum_{i=1}^{N} \omega_{ij}^{\frac{1}{\epsilon_{M_j}}} M_{ij}^{\rho_{M_j}} \Big)^{\frac{1}{\rho_{M_j}}} \right).$$

Taking first order conditions with respect to M_{ij} and rearranging yields

$$\Delta \log \left(\frac{P_{it} M_{ijt}}{P_{jt}^{M} M_{jt}} \right) = (1 - \epsilon_{M_j}) \Delta \log \left(\frac{P_{it}}{P_{jt}^{M}} \right). \tag{14}$$

Combining Equations (13) and (14) yields Equation (6).

Model's propositions: flexibility and frictions

We proceed to find an analytical expression for sector's 2 Lagrange multiplier μ_2. To this end, we need to solve for sectoral prices and input demand, using input optimality conditions, binding working capital constraints, and market clearing conditions.

Assume the wage rate is the numeraire ($w = 1$). From the production function of sector 1 ($Q_1 = Z_1 L_1$) and from the binding constraint in sector 1 ($L_1 = \eta_1 P_1 Q_1$), we obtain

$$P_1 = \frac{1}{\eta_1 Z_1}.$$

Using the market clearing condition for the consumption good ($Q_2 = C$), the market clearing condition for (inelastic) labor ($\bar{L} = L_1 + L_2 = 1$), and the household budget constraint $\bar{L} = P_2 C$, we obtain

$$P_2 = \frac{1}{Q_2}.$$

The binding constraint of sector 2 and the market clearing condition for sector 1's goods ($Q_1 = M_{12}$) imply

$$\theta_2^w L_2 + \theta_{12}^m P_1 Q_1 = \eta_2 P_2 Q_2,$$

$$\theta_2^w L_2 + \theta_{12}^m \frac{1 - L_2}{\eta_1} = \eta_2,$$

and that

$$L_2 = \frac{\eta_1 \eta_2 - \theta_{12}^m}{\eta_1 \theta_2^w - \theta_{12}^m}.$$

Having solved for L_1, L_2 we obtain

$$Q_1 = M_{12} = Z_1 L_1$$

and

$$Q_2 = Z_2\Big(a^{1-\rho_Q} L_1^{\rho_Q} + (1-a)^{1-\rho_Q} M_{12}^{\rho_Q}\Big)^{\frac{1}{\rho_Q}},$$

where $\rho_Q = \Big(\epsilon_Q - 1\Big)/\epsilon_Q$. Finally, using first order and necessary condition (FONC) in the use of labor or intermediates for firms in sector 2:

$$P_2 Z_2^{\rho_Q}\Big(\frac{aQ_2}{L_2}\Big)^{1-\rho_Q} - \frac{(1+\mu_2\theta_2^w)}{(1+\mu_2\eta_2)} = 0,$$

$$P_2 Z_2^{\rho_Q}\Big(\frac{(1-a)Q_2}{M_{12}}\Big)^{1-\rho_Q} - P_1\frac{(1+\mu_2\theta_{12}^m)}{(1+\mu_2\eta_2)} = 0,$$

we can solve for μ_2.

Proof of Proposition 1.

Constraint on intermediates: set $\theta_2^w = 0$ and $\theta_{12}^m = 1$, which implies $L_2 = 1-\eta_1\eta_2$ and $Q_1 = Z_1\eta_1\eta_2$. From the FONC for L_2, and from the fact that $P_2 = \frac{1}{Q_2}$, we obtain

$$\Big(\frac{Q_2}{Z_2}\Big)^{\rho_Q} = (1+\mu_2\eta_2)\Big(\frac{a_2}{L_2}\Big)^{1-\rho_Q}.$$

Similarly, using the production function for sector 2 we obtain

$$\Big(\frac{Q_2}{Z_2}\Big)^{\rho_Q} = a_2^{1-\rho_Q} L_2^{\rho_Q} + (1-a_2)^{1-\rho_Q} Q_1^{\rho_Q},$$

implying

$$(1+\mu_2\eta_2)\Big(\frac{a_2}{L_2}\Big)^{1-\rho_Q} = a_2^{1-\rho_Q} L_2^{\rho_Q} + (1-a_2)^{1-\rho_Q} Q_1^{\rho_Q},$$

$$(1+\mu_2\eta_2)\Big(\frac{a_2}{(1-\eta_1\eta_2)}\Big)^{1-\rho_Q} = a_2^{1-\rho_Q}(1-\eta_1\eta_2)^{\rho_Q} + (1-a_2)^{1-\rho_Q}(Z_1\eta_1\eta_2)^{\rho_Q},$$

and

$$\mu_2 = \left(\frac{(1-\eta_1\eta_2)\,(1-a_2)}{a_2\eta_2}\right)^{1-\rho_Q}(\eta_1 Z_1)^{\rho_Q} - \eta_1.$$

Therefore,

$$\frac{\partial\mu_2}{\partial\epsilon_Q} = \frac{1}{\epsilon_Q^2}\eta_1 Z_1^{\rho_Q}\phi_m^{1-\rho_Q}\ln\left(\frac{Z_1}{\phi_m}\right),$$

where $\phi_m = \frac{(1-\eta_1\eta_2)(1-a_2)}{\eta_1\eta_2 a_2}$. If $\frac{Z_1}{\phi_m}$ the derivative is negative, otherwise it is positive.

Constraint on labor: now set $\theta_2^w = 1$ and $\theta_{12}^m = 0$, which implies $L_2 = \eta_2$ and $Q_1 = Z_1(1-\eta_2)$. From the FONC for M_{12}, and from the fact that $P_2 = \frac{1}{Q_2}$ and $P_1 = \frac{1}{Z_1\eta_1}$, we obtain

$$\Big(\frac{Q_2}{Z_2}\Big)^{\rho_Q} = Z_1\eta_1(1+\mu_2\eta_2)\Big(\frac{(1-a_2)}{M_{12}}\Big)^{1-\rho_Q}.$$

Again using the production function we obtain

$$\Big(\frac{Q_2}{Z_2}\Big)^{\rho_Q} = a_2^{1-\rho_Q} L_2^{\rho_Q} + (1-a_2)^{1-\rho_Q} M_{12}^{\rho_Q},$$

which implies

$$(1+\mu_2\eta_2)\Big(\frac{(1-a_2)}{M_{12}}\Big)^{1-\rho_Q} Z_1\eta_1 = a_2^{1-\rho_Q} L_2^{\rho_Q} + (1-a_2)^{1-\rho_Q} M_{12}^{\rho_Q},$$

$$(1+\mu_2\eta_2)\Big(\frac{(1-a_2)}{Z_1(1-\eta_2)}\Big)^{1-\rho_Q} Z_1\eta_1 = a_2^{1-\rho_Q} \eta_2^{\rho_Q} + (1-a_2)^{1-\rho_Q} Z_1(1-\eta_2)^{\rho_Q},$$

and

$$\mu_2 = \left(\frac{(1-\eta_2)\,a_2}{(1-a_2)\,\eta_2}\right)^{1-\rho_Q} \frac{1}{\eta_1} Z_1^{-\rho_Q} + \frac{(1-\eta_1-\eta_2)}{\eta_1\eta_2}.$$

Therefore,

$$\frac{\partial\mu_2}{\partial\epsilon_Q} = -\frac{1}{\epsilon_Q^2}\frac{1}{\eta_1} Z_1^{-\rho_Q}\phi_w^{1-\rho_Q}\ln\left(Z_1\phi_w\right),$$

where $\phi_w = \frac{(1-\eta_2)a_2}{\eta_2(1-a_2)}$. If $Z_1\phi_w > 1$ the derivative is negative, otherwise it is positive. ∎

Proof of Proposition 2.

Constraint on intermediates: Set $\theta_2^w = 0$ and $\theta_{12}^m = 1$. Suppose sector 1 is constrained. From Proposition 1 we have

$$\mu_2 = \left(\frac{(1-\eta_1\eta_2)\,(1-a_2)}{a_2\eta_2}\right)^{1-\rho_Q} (\eta_1 Z_1)^{\rho_Q} - \eta_1.$$

We define Z_1^* as the sector 1 productivity that results in sector 2 being exactly constrained, with $\mu_2 = 0$. Therefore,

$$Z_1^* = \phi_m^{\frac{1}{1-\epsilon_Q}},$$

so that

$$\frac{\partial Z_1^*}{\partial\epsilon_Q} = \phi_m^{\frac{1}{1-\epsilon_Q}} \frac{1}{\left(1-\epsilon_Q\right)^2}\ln\left(\phi_m\right).$$

The sign depends on whether ϕ_m is larger or smaller than 1. The interpretation depends on ϕ_m but also on whether ϵ_Q is smaller or larger than 1. When $\phi_m < 1$, within the group of firms with $\epsilon_Q < 1$, $\frac{\partial Z_1^*}{\partial\epsilon_Q} < 0$ means that more flexible sectors need a more negative shock to input suppliers in order to become constrained.

Constraint on labor: On the other hand, if $\theta_{12}^{m}=0$ and $\theta_{2}^{w}=1$, we have

$$\mu_2=\left(\frac{(1-\eta_2)\,a_2}{(1-a_2)\,\eta_2}\right)^{1-\rho_Q}\frac{1}{\eta_1}Z_1^{-\rho_Q}+\frac{(1-\eta_1-\eta_2)}{\eta_1\eta_2}.$$

$$Z_1^{*}=\phi_w^{\frac{1}{\epsilon_Q-1}},$$

so that

$$\frac{\partial Z_1^{*}}{\partial\epsilon_Q}=-\phi_w^{\frac{1}{\epsilon_Q-1}}\left(\frac{\eta_1+\eta_2-1}{\eta_2}\right)^{\frac{\epsilon_Q}{\epsilon_Q-1}}\frac{1}{\left(\epsilon_Q-1\right)^2}\ln\left(\frac{\eta_2\phi_w}{\eta_1+\eta_2-1}\right).$$

The sign depends on whether $\frac{\eta_2\phi_w}{\eta_1+\eta_2-1}$ is smaller or larger than 1. The interpretation depends on $\frac{\eta_2\phi_w}{\eta_1+\eta_2-1}$, and also depends on whether ϵ_Q is smaller or larger than 1. When $\frac{\eta_2\phi_w}{\eta_1+\eta_2-1}<1$, within the group of firms with $\epsilon_Q>1$, $\frac{\partial Z_1^{*}}{\partial\epsilon_Q}>0$ means that more flexible sectors need a smaller negative shock to input suppliers in order to become constrained. ■

Proof of Proposition 2.1: η_1^{*}.

Constraint on intermediates: set $\theta_{2}^{w}=0$ and $\theta_{12}^{m}=1$. Suppose sector 1 is constrained. From Proposition 1 we have:

$$\mu_2=\left(\frac{(1-\eta_1\eta_2)\,(1-a_2)}{a_2\eta_2}\right)^{1-\rho_Q}(\eta_1Z_1)^{\rho_Q}-\eta_1.$$

We define η_1^{*} as the sector 1 collateral constraint parameter that results in sector 2 being exactly constrained, with $\mu_2=0$. Therefore,

$$\eta_1^{*}=\frac{(1-a_2)Z_1^{\epsilon_Q-1}}{a_2\eta_2+(1-a_2)\eta_2Z_1^{\epsilon_Q-1}}.$$

If $Z_1=1$, $\frac{\partial\eta_1^{*}}{\partial\epsilon_Q}=0$. If $Z_1>11$, $\frac{\partial\eta_1^{*}}{\partial\epsilon_Q}>0$. If $Z_1<1$, $\frac{\partial\eta_1^{*}}{\partial\epsilon_Q}<0$.

Constraint on labor: On the other hand, if $\theta_{12}^{m}=0$ and $\theta_{2}^{w}=1$, we have

$$\mu_2=\left(\frac{(1-\eta_2)\,a_2}{(1-a_2)\,\eta_2}\right)^{1-\rho_Q}\frac{1}{\eta_1}Z_1^{-\rho_Q}+\frac{(1-\eta_1-\eta_2)}{\eta_1\eta_2}.$$

$$\eta_1^{*}=\eta_2\phi_w^{\frac{1}{\epsilon_Q}}Z_1^{-\rho_Q}+1-\eta_2,$$

so that

$$\frac{\partial \eta_1^*}{\partial \epsilon_Q} = -\eta_2 \frac{1}{\epsilon_Q^2} \phi_w^{\frac{1}{\epsilon_Q}} \ln(\phi_w Z_1).$$

The sign depends on whether $Z_1\phi_w$ is smaller or larger than 1. The interpretation depends on $Z_1\phi_w$, and also depends on whether ϵ_Q is smaller or larger than 1. When $Z_1\phi_w < 1$, within the group of firms with $\epsilon_Q > 1$, $\frac{\partial \eta_1^*}{\partial \epsilon_Q} > 0$ means that more flexible sectors need a smaller negative shock to input suppliers in order to become constrained. ■

Appendix B: Tables

Table 7.1
U.S. Sectors 2014 (BEA)

Sector Number	Iocode	Sector Name	Capital	Labor	Intermediates	Sales Share
1	111CA	Farms	34%	7%	59%	1.41%
2	113FF	Forestry, fishing, and related activities	30%	42%	28%	0.17%
3	211	Oil and gas extraction	61%	9%	30%	1.39%
4	212	Mining, except oil and gas	48%	14%	38%	0.42%
5	213	Support activities for mining	26%	41%	33%	0.34%
6	22	Utilities	49%	18%	33%	1.35%
7	23	Construction	20%	35%	45%	3.89%
8	321	Wood products	10%	20%	71%	0.32%
9	327	Nonmetallic mineral products	18%	22%	60%	0.38%
10	331	Primary metals	10%	11%	79%	0.91%
11	332	Fabricated metal products	13%	25%	61%	1.22%
12	333	Machinery	14%	23%	63%	1.31%
13	334	Computer and electronic products	35%	34%	31%	1.25%
14	335	Electrical equipment, appliances, and components	16%	27%	57%	0.41%
15	3361MV	Motor vehicles, bodies and trailers, and parts	13%	11%	76%	1.92%
16	3364OT	Other transportation equipment	15%	22%	64%	1.12%
17	337	Furniture and related products	9%	26%	65%	0.23%
18	339	Miscellaneous manufacturing	19%	29%	52%	0.54%
19	311FT	Food and beverage and tobacco products	15%	10%	75%	3.13%
20	313TT	Textile mills and textile product mills	9%	22%	69%	0.18%
21	315AL	Apparel and leather and allied products	6%	21%	72%	0.13%
22	322	Paper products	13%	15%	71%	0.63%
23	323	Printing and related support activities	14%	30%	55%	0.28%
24	324	Petroleum and coal products	19%	2%	79%	2.64%
25	325	Chemical products	33%	12%	56%	2.62%
26	326	Plastics and rubber products	14%	18%	68%	0.75%
27	42	Wholesale trade	35%	31%	34%	5.09%
28	441	Motor vehicle and parts dealers	31%	41%	28%	0.81%
29	445	Food and beverage stores	28%	39%	32%	0.72%
30	452	General merchandise stores	26%	39%	35%	0.72%
31	4A0	Other retail	29%	31%	39%	2.76%
32	481	Air transportation	21%	23%	55%	0.61%
33	482	Rail transportation	27%	25%	48%	0.29%
34	483	Water transportation	18%	11%	71%	0.20%
35	484	Truck transportation	15%	26%	59%	1.07%
36	485	Transit and ground passenger transportation	25%	32%	42%	0.18%
37	486	Pipeline transportation	57%	19%	23%	0.11%
38	487OS	Other transportation and support activities	19%	33%	48%	0.70%
39	493	Warehousing and storage	15%	42%	43%	0.29%
40	511	Publishing industries, except internet	31%	32%	36%	1.07%
41	512	Motion picture and sound recording industries	54%	21%	25%	0.49%
42	513	Broadcasting and telecommunications	36%	14%	50%	2.65%
43	514	Data processing, internet pub., and other inf. servi	19%	24%	57%	0.67%
44	521CI	Federal Reserve banks, credit interm., and rel. act.	38%	32%	31%	2.28%
45	523	Securities, commodity contracts, and investments	4%	47%	49%	1.55%
46	524	Insurance carriers and related activities	26%	28%	47%	2.73%
47	525	Funds, trusts, and other financial vehicles	26%	1%	73%	0.49%
48	HS	Housing Services	90%	1%	9%	5.88%
49	ORE	Other Real Estate	33%	8%	59%	3.09%
50	532RL	Rental and leasing services and lessors of int. asse	46%	10%	44%	1.10%
51	5411	Legal services	33%	39%	28%	0.99%
52	5415	Computer systems design and related services	10%	60%	29%	1.14%
53	5412OP	Miscellaneous professional, scientific, and tech. S	17%	42%	42%	4.00%
54	55	Management of companies and enterprises	8%	48%	44%	1.93%
55	561	Administrative and support services	18%	47%	35%	2.41%
56	562	Waste management and remediation services	19%	28%	53%	0.30%
57	61	Educational services	7%	54%	40%	1.03%
58	621	Ambulatory health care services	13%	50%	37%	3.01%
59	622	Hospitals	6%	46%	49%	2.45%
60	623	Nursing and residential care facilities	7%	53%	39%	0.72%
61	624	Social assistance	9%	55%	36%	0.55%
62	711AS	Performing arts, spectator sports, museums	28%	32%	40%	0.50%
63	713	Amusements, gambling, and recreation industries	24%	33%	43%	0.45%
64	721	Accommodation	30%	32%	38%	0.73%
65	722	Food services and drinking places	16%	36%	48%	2.15%
66	81	Other services, except government	17%	43%	41%	2.07%
67	GFGD	Federal general government (defense)	26%	38%	36%	2.02%

Table 7.2
Elasticities IV 1997-2014 (different instruments)

VARIABLES	(1) IV1	(2) IV1	(3) $IV1^{exc}$	(4) IV2	(5) IV2	(6) $IV2^{exc}$
$\epsilon_M - 1$	-0.32	-0.28	3.74**	-0.82**	-0.99**	0.67**
	(0.83)	(0.82)	(0.04)	(0.04)	(0.01)	(0.03)
$\epsilon_Q - 1$	2.82	1.82	2.86	0.83*	1.29**	2.08***
	(0.20)	(0.48)	(0.34)	(0.08)	(0.01)	(0.00)
Observations	26,398	26,398	26,000	23,098	23,098	22,750
Number of partner	1,650	1,650	1,625	1,650	1,650	1,625
Year FE	No	Yes	Yes	No	Yes	Yes
F Kleibergen-Paap	6.45	5.66	3.42	28.13	29.59	13.63
P-value Hansen test	0.69	0.97	0.01	0.06	0.14	0.00

IV1 only uses military instruments. IV2 adds two lags of endogenous variables.

Table 7.3
Elasticities IV 1997-2007

VARIABLES	(1) FE	(2) FE	(3) FE^{exc}	(4) IV	(5) IV	(6) IV^{exc}
$\epsilon_M - 1$	-0.36***	-0.37***	-0.25***	-3.05***	-2.71***	-0.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.77)
$\epsilon_Q - 1$	-0.14	-0.09	0.08	1.42*	0.70	2.54***
	(0.24)	(0.43)	(0.44)	(0.06)	(0.38)	(0.00)
Observations	15,975	15,975	15,750	11,550	11,550	11,375
Number of partner	1,775	1,775	1,750	1,650	1,650	1,625
Year FE	No	Yes	Yes	No	Yes	Yes
F Kleibergen-Paap				59.12	54.84	25.95
P-value Hansen test				0.00	0.00	0.00

Note: P-value in parentheses. Stock-Yogo test critical value 10%: 13.43. *exc* excludes the Petroleum industry.

Table 7.4
Elasticities IV 1997-2007 (different instruments)

VARIABLES	(1) IV1	(2) IV1	(3) $IV1^{exc}$	(4) IV2	(5) IV2	(6) $IV2^{exc}$
$\epsilon_M - 1$	-1.21	-1.33	-0.55	-3.05***	-2.71***	-0.12
	(0.34)	(0.32)	(0.69)	(0.00)	(0.00)	(0.77)
$\epsilon_Q - 1$	8.12***	6.22***	10.87***	1.42*	0.70	2.54***
	(0.00)	(0.00)	(0.00)	(0.06)	(0.38)	(0.00)
Observations	14,850	14,850	14,625	11,550	11,550	11,375
Number of partner	1,650	1,650	1,625	1,650	1,650	1,625
Year FE	No	Yes	Yes	No	Yes	Yes
F Kleibergen-Paap	9.46	8.33	13.20	59.12	54.84	25.95
P-value Hansen test	0.18	0.04	0.17	0.00	0.00	0.00

IV1 only uses military instruments. IV2 adds two lags of endogenous variables.

Table 7.5
Descriptive Statistics 2009q1 Service

	mean	sd	min	p25	p75	max
GZ spread	7.85	5.65	2.33	5.00	8.98	25.93
Debt to sales	2.92	3.38	0.35	1.04	3.18	15.51
Debt to assets	0.38	0.15	0.13	0.26	0.48	0.75
Sales	703.52	1285.33	84.76	137.07	793.60	6111.18
Value Inventories	221.69	519.05	1.88	10.08	140.77	2473.45
Working Cap. to Sales	0.33	0.31	0.01	0.08	0.61	1.20
Value Plant	1231.98	1612.37	51.00	90.01	1415.74	5348.49

Table 7.6
Descriptive Statistics 2009q1 Manufacturing

	mean	sd	min	p25	p75	max
GZ spread	6.66	4.21	2.53	3.17	8.61	19.35
Debt to sales	1.54	0.48	0.78	1.25	1.89	2.64
Debt to assets	0.32	0.07	0.19	0.29	0.34	0.48
Sales	354.82	336.38	97.69	163.72	365.10	1558.30
Value Inventories	197.62	112.71	66.37	101.45	294.77	446.96
Working Cap. to Sales	0.80	0.36	0.18	0.51	1.04	1.47
Value Plant	563.81	963.45	86.55	166.60	546.77	4346.96

Table 7.7
Top-20 sectors in terms of flexibility (Decline in GDP in 2009)

Sector	**Centrality**	**Stat. Adjusted ϵ_Q**
Food and beverage and tobacco products	2.34%	1.0
Petroleum and coal products	2.09%	0.1
Other Real Estate	1.81%	2.2
Construction	1.74%	1.0
Wholesale trade	1.72%	3.2
Miscellaneous professional, scientific, and tech. Serv.	1.66%	1.0
Motor vehicles, bodies and trailers, and parts	1.47%	1.0
Chemical products	1.45%	0.1
Broadcasting and telecommunications	1.32%	1.0
Insurance carriers and related activities	1.28%	1.0
Hospitals	1.19%	2.4
Ambulatory health care services	1.10%	1.0
Other retail	1.08%	2.2
Food services and drinking places	1.03%	1.0
Administrative and support services	0.85%	5.5
Management of companies and enterprises	0.84%	2.2
Other services, except government	0.84%	3.0
Farms	0.83%	1.0
Machinery	0.82%	2.3
Securities, commodity contracts, and investments	0.76%	3.2

Note: Sectoral centrality is measured as the difference between i) the decline in GDP in 2009 if all sectors have Cobb-Douglas technologies ($\epsilon_{Q_i} = 1$ for all i) and ii) the implied decline in GDP in 2009 if sector i has $\epsilon_{Q_i} = 2$ (with $\epsilon_{Q_j} = 1$ for all $j \neq i$).

Appendix C: Figures

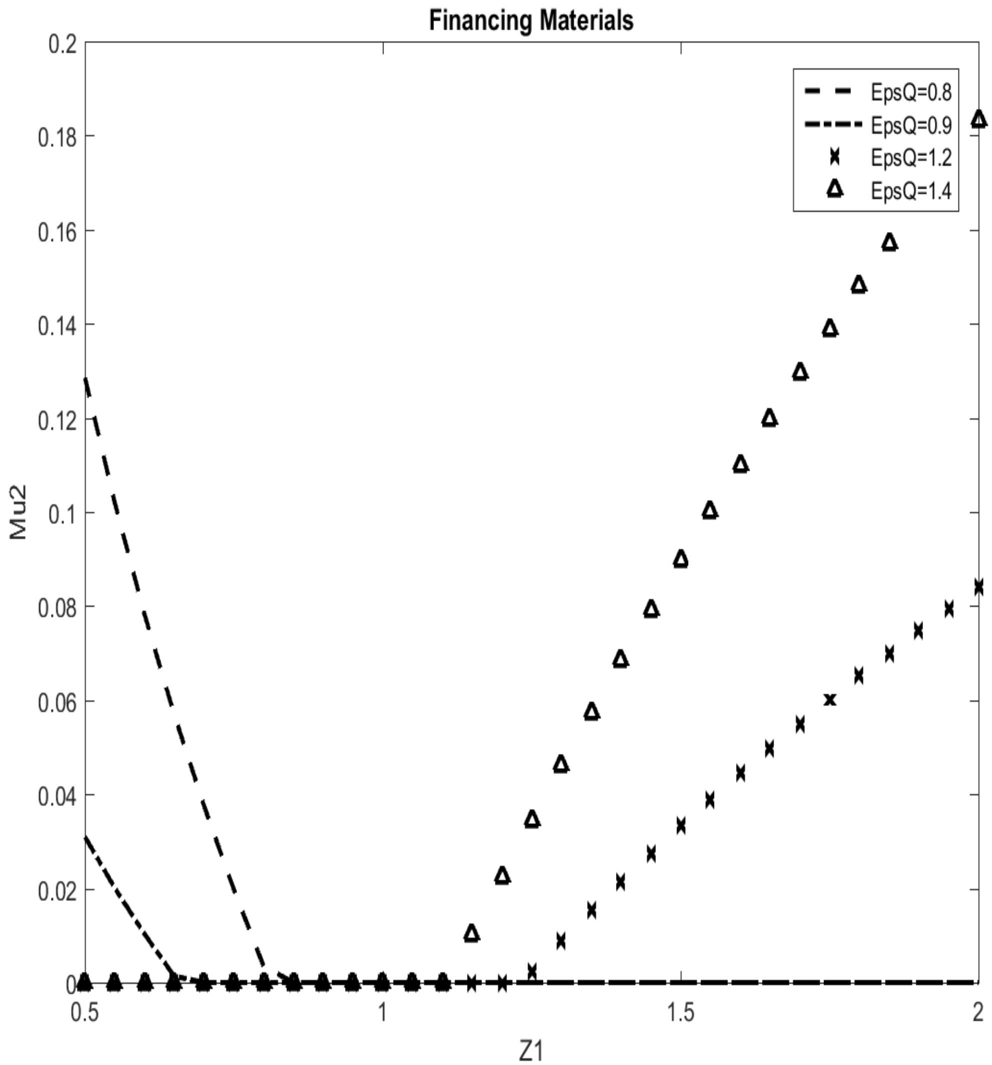

Figure 7
Lagrange Multiplier. Constraint on Intermediates $\phi_m < 1$

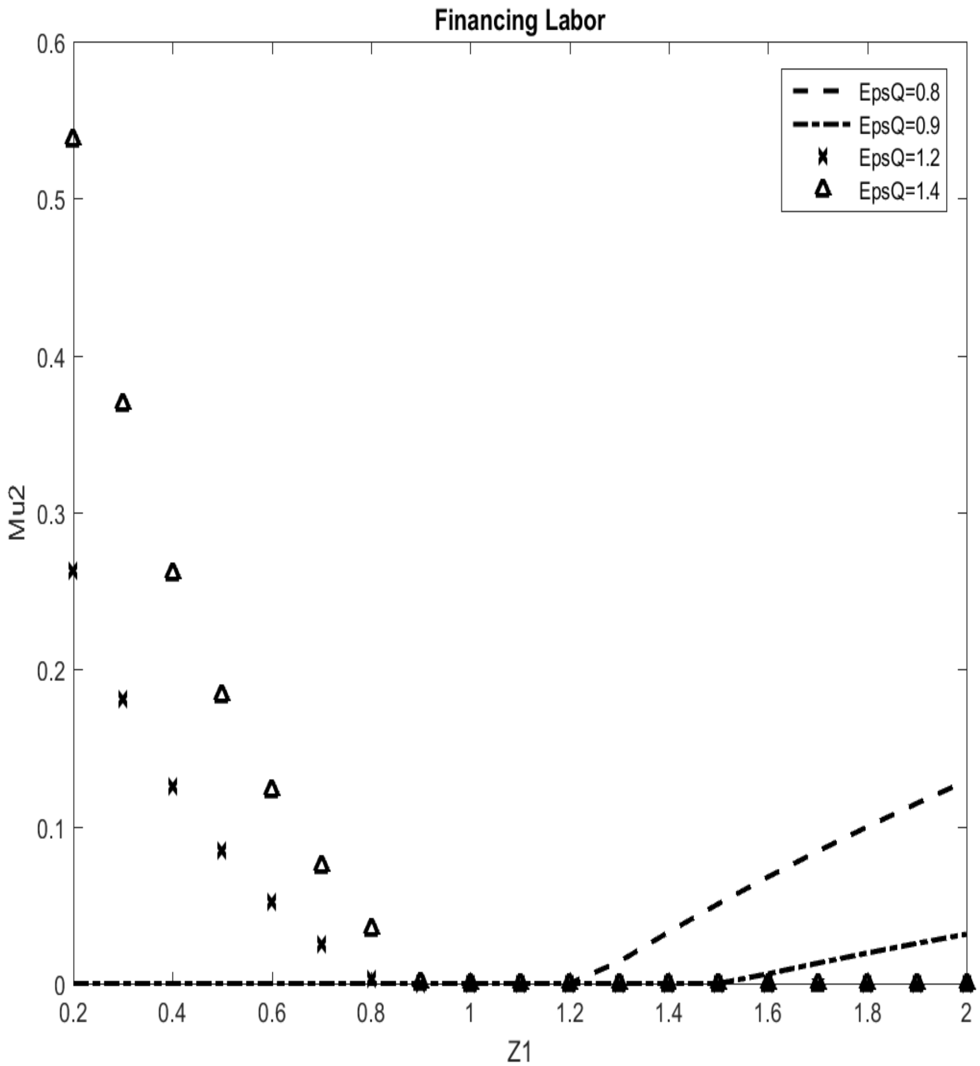

Figure 8
Lagrange Multiplier. Constraint on Labor $\phi_w < 1$

Figure 9
Relative Price Intermediates and Value Added: Manufacturing sectors

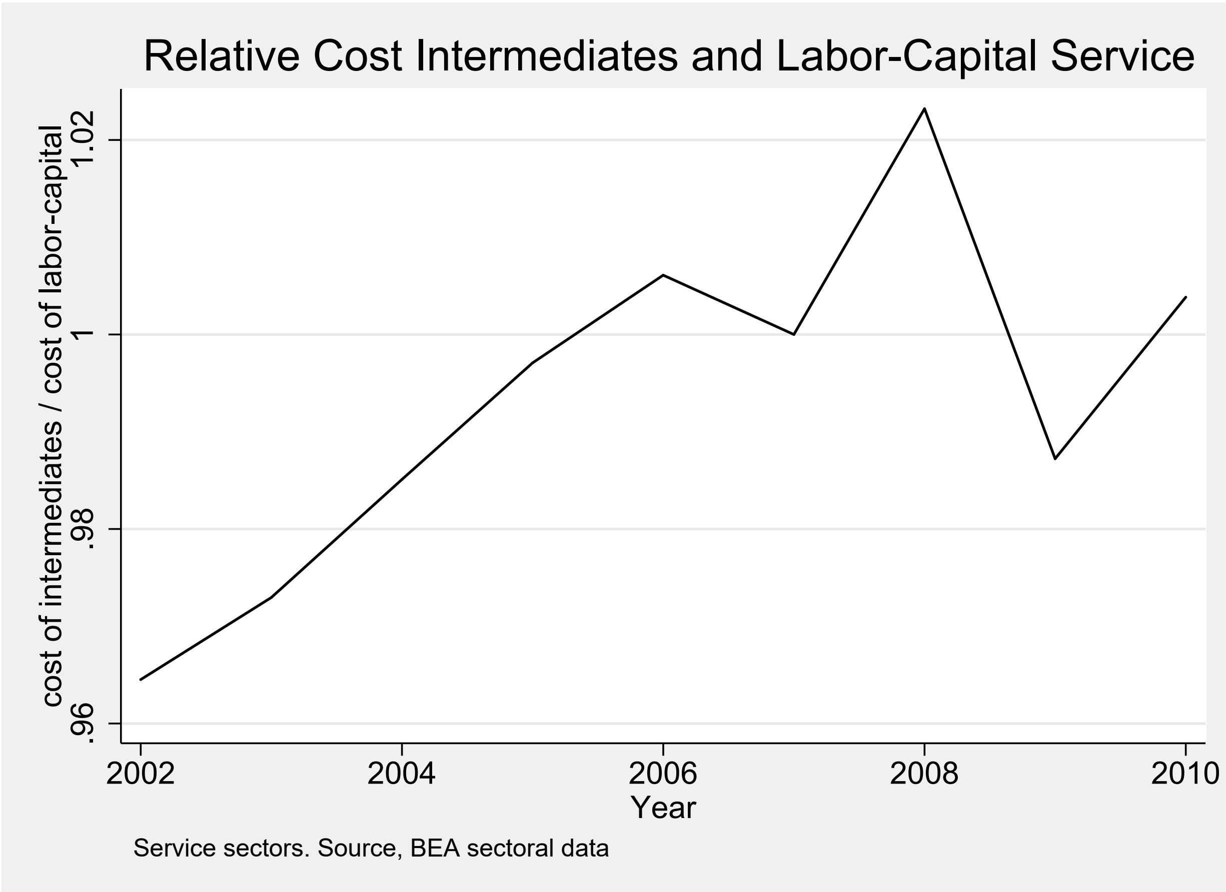

Figure 10
Relative Price Intermediates and Value Added: Service sectors

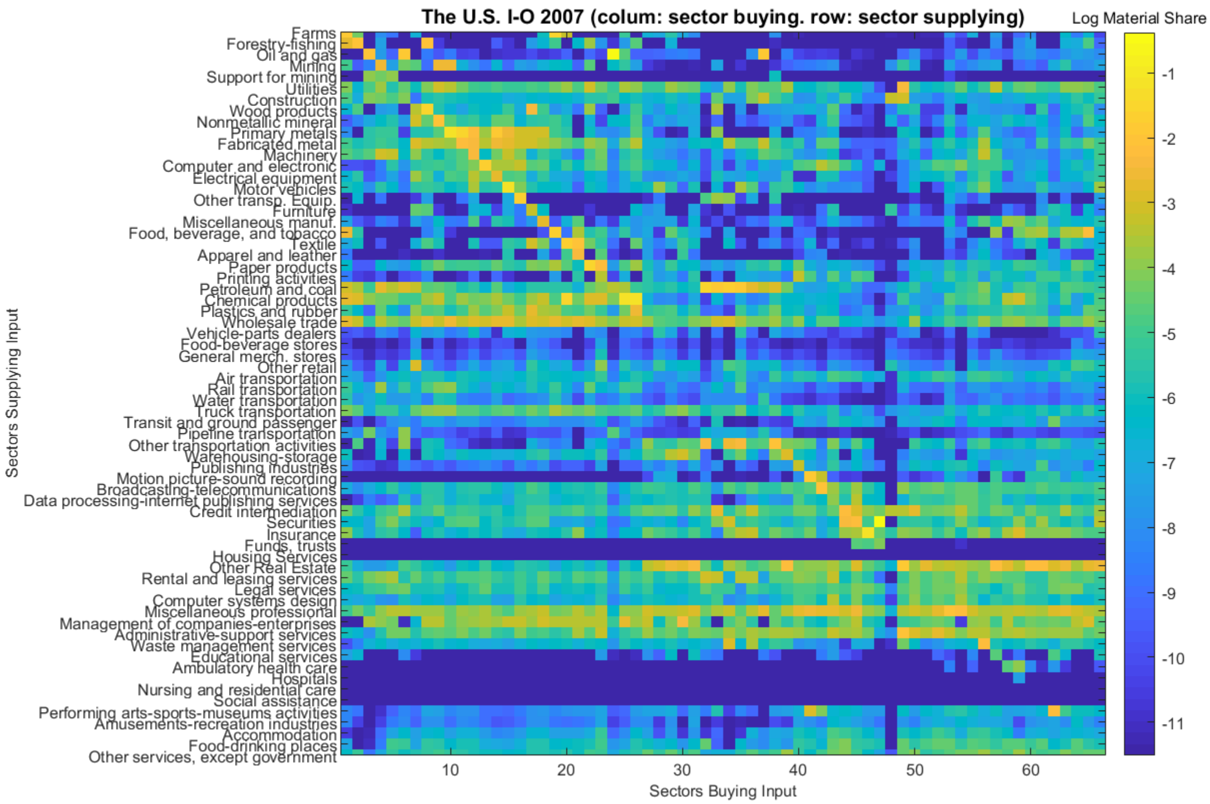

Figure 11
USA production network 2007

Appendix D: OLS bias and IV validity

OLS bias in estimating elasticities

Rewrite Equation (6) in general form

$$Y = \beta X + \gamma Z + \nu,$$

where X contains sectoral prices and Z has unobserved productivity and credit wedges. In practice, we estimate

$$Y = \beta X + \varrho$$

via OLS, which implies the following OLS bias

$$\tilde{\beta}^{OLS} = \beta + \gamma\delta,$$

where $\gamma\delta$ is the bias. The parameter γ is the true effect of the unobserved variables (Z) on sectoral input shares (Y). On the other hand, $\delta \approx cov(X, Z)$. Hence, to characterize the bias we need to understand the theoretical relationship between Z intermediate input shares (Y) and relative prices (X).

Let's first analyze the effect of productivity on intermediate input shares and prices. From Equation (6) we know that the relationship between productivities and intermediate input shares is given by $(\epsilon_Q - 1)\Delta \log Z_{jt}$. Theoretically, if firms are flexible in substituting labor for intermediates ($\epsilon_Q > 1$), increases in Z_{jt} lead to increases in gross output and therefore increases in intermediate input demand. The opposite occurs when $\epsilon_Q < 1$. On the other hand, the relationship between productivity and sectoral prices is negative. In competitive markets, an increase in the productivity of firms in sector j, all else equal, increases the supply of Q_j which then leads to a decrease in P_j. Therefore, if the only source of bias is unobserved productivity, there is a downward bias in the estimation of elasticities – $\delta\gamma < 0$ – if $\epsilon_Q > 1$, and there is an upward bias if $\epsilon_Q < 1$.

To understand how the credit wedge relates to input shares, rewrite the constraint as

$$wL_j + \tilde{\theta}_j^m P_j^M M_j \leq \tilde{\eta}_j P_j Q_j,$$

where $\tilde{\theta}_j^m = \theta_j^m / \theta_j^l$ and $\tilde{\eta}_j^m = \eta_j / \theta_j^l$. In this case, the first order conditions imply $\bar{\mu}_{jt} = \frac{1+\mu_{jt}\tilde{\eta}_j}{1+\mu_{jt}\tilde{\theta}_j^m}$. When firms are unconstrained ($\mu_j = 0$), $\bar{\mu}_{jt}$ is 1 , meaning that $\Delta\bar{\mu}_{jt} = 0$. When the constraint binds, an increase in μ_j can decreases or decrease $\bar{\mu}_j$, and therefore increase or decrease intermediate input demand according to Equation (6), depending on whether $\tilde{\theta}_j^m$ is smaller or larger than $\tilde{\eta}_j$. When $\tilde{\theta}_j^m > \tilde{\eta}_j$, conditional on the collateral constraint parameter η, the constraint is relatively tighter on intermediates, therefore a reduction in credit availability (reduction in η_j, for example) will induce a further decrease in intermediates demand. However, if $\tilde{\theta}_j^m < \tilde{\eta}_j$, the constraint is relatively tighter in labor, implying tighter credit conditions will involve the firm substituting away the more constrained input (labor) toward the less constrained input, in this case intermediate inputs.

In the previous analysis, we held the external funding constraint (represented by η) constant. However, if we instead hold constant θ_j^l and θ_j^m, a low η_j implies $\tilde{\theta}_j^m > \tilde{\eta}_j$, which means that a tighter constraint generates a downward bias in the OLS estimates.

Validity and strength of IV

We now proceed to analyze whether our IV approach is able to correct for the endogeneity. We know from our theory that for sectors with $\epsilon_Q > 1$ our FE estimates should be downward biased, while for sectors with $\epsilon_Q > 1$ the bias depends on whether frictions are binding or not. When frictions are not binding, if $\epsilon_Q > 1$, unobserved productivities bias elasticities estimates upward. In Figure 13 we plot the FE and IV estimates of ϵ_Q for the sample 1997-2014. We plot the 45 degree line to visualize the downward or upward bias from the OLS estimates. In the left panel we plot the elasticities for sectors with $\hat{\epsilon}_Q^{IV} < 1$, while in the right panel we plot sector with $\hat{\epsilon}_Q^{IV} > 1$. In general, we observe that, consistent with our theory, our IV estimates correct the upward bias of ϵ_Q if $\hat{\epsilon}_Q^{IV} < 1$ and correct the downward bias if $\hat{\epsilon}_Q^{IV} > 1$.

We find similar results using the sample 1997-2007 in Figure 14. In the left panel we plot the elasticities for sectors with $\hat{\epsilon}_Q^{IV} < 1$, while in the right panel we plot sector with $\hat{\epsilon}_Q^{IV} > 1$. In general, we observe that, consistent with our theory, our IV estimates correct the upward bias of ϵ_Q if $\hat{\epsilon}_Q^{IV} < 1$ and correct the downward bias if $\hat{\epsilon}_Q^{IV} > 1$.

We know look into the strength of the first stage estimation and the precision of the second stage estimates. In Figure 15 we plot the first stage F-test (Kleibergne-Paap test) for our two endogenous variables. In general, the IV using the restricted sample yields stronger first stage estimation, especially in the estimation of ϵ_Q (panel B).

In Figure 16 we plot the second stage t-test – clustered at the intermediate-input partner level – for our two elasticities. In general, the IV using the restricted sample yields more precise sectoral elasticity estimates, which is also especially true when estimating ϵ_Q.

We proceed to compare the IV estimates of sectoral elasticities across sample periods. In Figure 12 we plot ϵ_M and ϵ_Q plus two standard deviation of the sectoral estimates. We drop the Housing sector as it displays quite large estimates for both elasticities when using data from the Great Recession. Across samples, the estimates of ϵ_M are highly correlated. There is also a positive, although weaker, correlation between the IV estimates of ϵ_Q across samples.

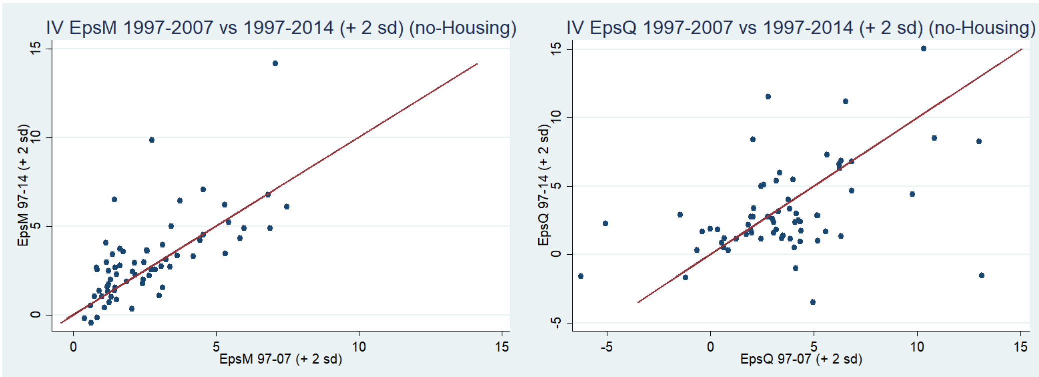

Figure 12
IV Elasticities Across Sample Periods +2 sd

It is instructive to look at what sectors display important differences in the estimation of ϵ_Q across samples. Wholesale trade and rental and leasing services have negative estimates when using the period 1997-2014, while they have large positive estimates when dropping data from the Great Recession ($\hat{\epsilon}_Q^{IV07} \approx 4$ and $\hat{\epsilon}_Q^{IV07} \approx 13$, respectively). The FE estimates suggest a similar pattern. The FE estimates using the whole sample are negative, while the FE estimates using the restricted sample are positive and larger than 4.

Our theory suggests that binding sectoral constraints downward bias the estimates of sectoral elasticities when either i) firms can pledge small fraction of their revenue or i) when the working capital constraint is equally important or more important for intermediates . This could generate the negative FE estimates. The fact that the IV estimates for the period 1997-2014 are also negative indicates that our instruments are not able to properly correct for the bias generated by the Great Recession. An additional concern when using data from the Great Recession is that the Housing sector displays extremely high elasticities.

Hence, our IV approach using the restricted sample is stronger, more precise, and also not contaminated with Great Recession bias. Given that our goal is to separately identify technologies from frictions, in the rest of our paper we use the the restricted sample in the estimation of sectoral elasticities. In the Appendix, we show that our main findings do not depend on this decision.

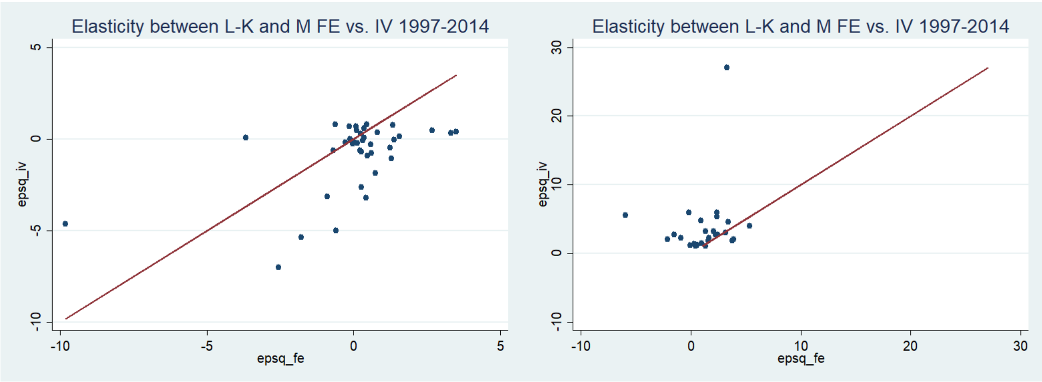

Figure 13
Bias in ϵ_Q, panel FE vs. IV 1997-2014 ($\epsilon_Q < 1$ and $\epsilon_Q > 1$)

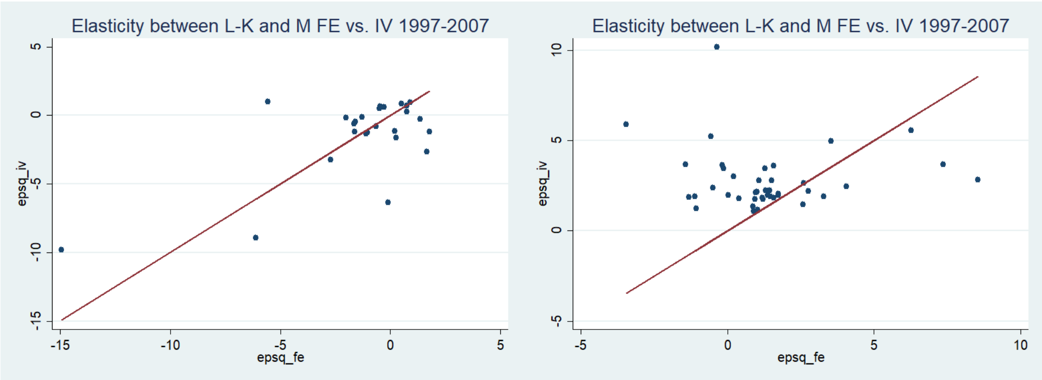

Figure 14
Bias in ϵ_Q, panel FE vs. IV 1997-2007 ($\epsilon_Q < 1$ and $\epsilon_Q > 1$)

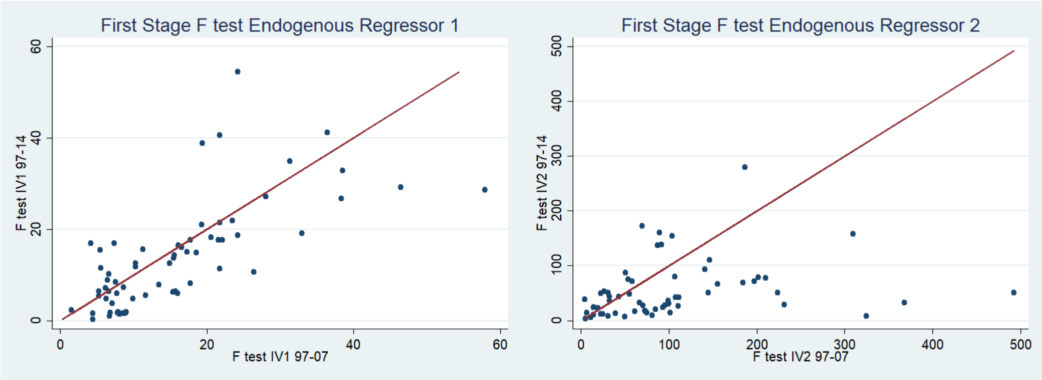

Figure 15
F test first stage

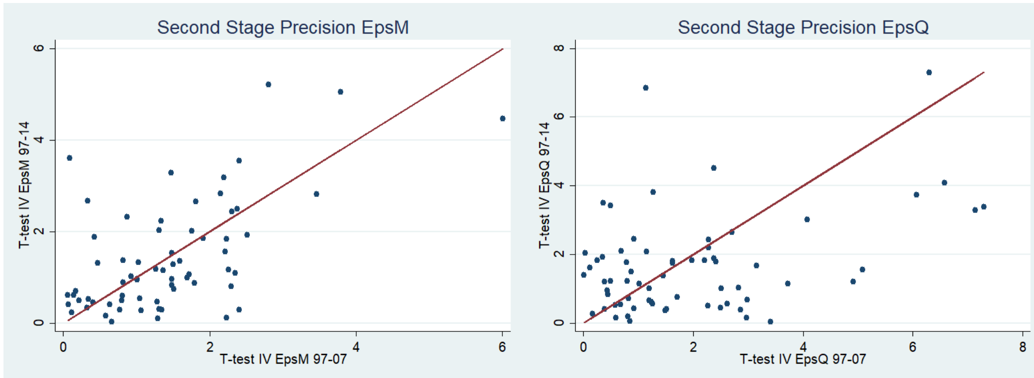

Figure 16
Precision second stage

Appendix E: Robustness checks, flexibility and spreads

In this Appendix, we show that the relationship between spreads and firm-level outcomes survives when we use different, and arguably more biased, approaches to estimate elasticities. The following tables use the IV 1997-2014 and panel FE 1997-2007 point estimates for all the 66 non-government sectors. In these tables, we also report the results for ϵ_M. Moreover, we report the results using debt to assets as a measure of leverage, rather than debt to sales. To simplify computation, rather than employing bootstrap we report the regressions using the elasticity point estimates or the elasticity point estimates adjusted by statistically significance. That is, if the elasticity estimate is not statistically significant, we set the elasticity to be unitary. In both cases, we set negative point estimates to be 1/1000. To simplify notation, we define L log leverage and ϵ_Q as log ϵ_Q.

Table 7.8 reports the results of our spread equation using a different measure of leverage and a different approach to account for the uncertainty in estimating elasticities (adjusting by statistically significance). Table 7.9 presents the spread regression using our main measure of leverage — debt to sales— but using our grouped FE 1997-2007 elasticities, adjusted by statistically significance.

Table 7.8
GZ spreads (grouped IV 1997-2007, statistically adjusted)

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) All	(5) Manufacturing	(6) Service
DR	0.71***	0.45***	0.69***	0.70***	0.52***	0.65***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L^{assets}	0.44***	0.75***	0.36***	0.51***	0.80***	0.40***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\epsilon_Q \cdot DR$	-0.02**	-0.03***	-0.03**	-0.02**	-0.05***	-0.03**
	(0.01)	(0.00)	(0.03)	(0.02)	(0.00)	(0.02)
$\epsilon_Q \cdot L^{assets}$	-0.05***	-0.07***	0.06*	-0.10***	-0.15***	0.06*
	(0.01)	(0.01)	(0.08)	(0.00)	(0.00)	(0.09)
Observations	2,493	989	1,376	2,356	933	1,295
R-squared	0.622	0.649	0.650	0.618	0.654	0.643
Number of sector	53	18	32	50	17	30
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

P-value in parentheses. Columns 4-6 excludes FIRE and Petroleum sectors.

Table 7.9
GZ Spreads (grouped FE 1997-2007, statistically adjusted)

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) All	(5) Manufacturing	(6) Service
DR	0.614***	0.364***	0.647***	0.573***	0.394***	0.609***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
L	0.551***	0.736***	0.762***	0.591***	0.736***	0.820***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\epsilon_Q \cdot D_R$	-0.012***	-0.017***	-0.017***	-0.016***	-0.022***	-0.021***
	(0.005)	(0.006)	(0.006)	(0.000)	(0.001)	(0.001)
$\epsilon_Q \cdot L$	0.023**	-0.028*	0.069***	0.026***	-0.031*	0.075***
	(0.011)	(0.074)	(0.000)	(0.006)	(0.095)	(0.000)
Observations	2,493	989	1,376	2,356	933	1,295
R-squared	0.623	0.650	0.647	0.618	0.650	0.642
Number of sector	53	18	32	50	17	30
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

P-value in parentheses. Columns 4-6 exclude FIRE and Petroleum sectors

Table 7.10 presents the spread regression using our main measure of leverage — debt to sales— but using our non-grouped IV 1997-2014 elasticities, without adjusting by statistically significance.

Table 7.10
GZ Spreads (non-grouped IV 1997-2014, not statistically adjusted)

VARIABLES	(1) All	(2) Manufacturing	(3) Service	(4) All	(5) Manufacturing	(6) Service
DR	0.700***	0.582***	0.685***	0.685***	0.642***	0.672***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L	0.477***	0.781***	0.518***	0.511***	0.779***	0.550***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\epsilon_Q \cdot D_R$	-0.005	-0.021***	-0.008	-0.004	-0.023***	-0.006
	(0.250)	(0.006)	(0.145)	(0.417)	(0.005)	(0.313)
$\epsilon_Q \cdot L$	0.009	-0.077***	0.025**	0.010	-0.081***	0.026**
	(0.290)	(0.000)	(0.050)	(0.249)	(0.000)	(0.044)
Observations	2,493	989	1,376	2,356	933	1,295
R-squared	0.622	0.656	0.642	0.615	0.654	0.634
Number of sector	53	18	32	50	17	30
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

P-value in parentheses. Columns 4-6 It exclude FIRE and Petroleum sectors.

Table 7.11 presents the spread regression using our main measure of leverage — debt to sales— but using our non-grouped FE 1997-2007 elasticities, without adjusting by statistically significance.

Table 7.11
GZ Spreads (non-grouped FE 1997-2007, not statistically adjusted)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	Manufacturing	Service	All	Manufacturing	Service
DR	0.673***	0.503***	0.717***	0.639***	0.561***	0.678***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L	0.411***	0.472***	0.757***	0.388***	0.271	0.801***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.142)	(0.000)
$\epsilon_Q \cdot D_R$	-0.005	-0.013**	0.001	-0.008**	-0.015**	-0.004
	(0.202)	(0.025)	(0.918)	(0.048)	(0.020)	(0.421)
$\epsilon_Q \cdot L$	-0.003	-0.071***	0.054***	-0.010	-0.098***	0.058***
	(0.731)	(0.000)	(0.000)	(0.299)	(0.000)	(0.000)
Observations	2,493	989	1,376	2,356	933	1,295
R-squared	0.620	0.657	0.642	0.614	0.658	0.635
Number of sector	53	18	32	50	17	30
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

P-value in parentheses. Columns 4-6 exclude FIRE and Petroleum sectors.

Table 7.12 presents the firm-level regression with revenues as dependent variable, using our main measure of leverage — debt to sales— but using our non-grouped IV 1997-2014 elasticities, without adjusting by statistically significance.

Table 7.12
Firms' revenue and flexibility (non-grouped IV 1997-2014, without adjusting by statistically significance)

VARIABLES	(1) All	(2) Manuf.	(3) Service
DR	0.387***	0.268***	0.387***
	(0.000)	(0.000)	(0.000)
L	0.010***	0.001	0.011***
	(0.000)	(0.507)	(0.000)
$\epsilon_Q \cdot D_R$	0.005***	-0.002	0.002**
	(0.000)	(0.191)	(0.045)
$\epsilon_Q \cdot L$	0.001***	0.002***	-0.001
	(0.001)	(0.000)	(0.197)
Observations	196,690	86,154	93,981
R-squared	0.266	0.352	0.233
Number of firm	9,136	3,896	4,327
Time FE	Yes	Yes	Yes

P-value in parentheses. Excludes FIRE sector firms.

Table 7.13 presents the firm-level regression with working capital as dependent variable, using our main measure of leverage — debt to sales— but using our non-grouped IV 1997-2014 elasticities, without adjusting by statistically significance.

Table 7.13
Firms' working capital and flexibility (non-grouped IV 1997-2014, without adjusting by statistically significance)

VARIABLES	(1) All	(2) Manuf.	(3) Service
DR	0.388***	0.285***	0.391***
	(0.000)	(0.000)	(0.000)
L	-0.109***	-0.113***	-0.108***
	(0.000)	(0.000)	(0.000)
$\epsilon_Q \cdot D_R$	0.007***	0.006***	0.004
	(0.000)	(0.005)	(0.206)
$\epsilon_Q \cdot L$	0.001**	0.004***	-0.002**
	(0.028)	(0.000)	(0.015)
Observations	150,424	78,381	63,721
R-squared	0.138	0.213	0.095
Number of firm	8,142	3,690	3,739
Time FE	Yes	Yes	Yes

P-value in parentheses. Excludes FIRE sector firms.