Entry Costs and the Macroeconomy*

Germán Gutiérrez† Callum Jones‡ Thomas Philippon§

February 2019

Abstract

We propose a model to identify the causes of rising profits and concentration, and declining entry and investment in the US economy. Our approach combines a rich structural DSGE model with cross-sectional identification from firm and industry data. Using asset prices, our model estimates the realized and anticipated shocks that drive the endogeneity of entry and concentration and recovers shocks to entry costs. We validate our approach by showing that the model-implied entry shocks correlate with independently constructed measures of entry regulation and M&A activities. We conclude that entry costs have risen and that the ensuing decline in competition has depressed consumption by five to ten percent.

Keywords: Corporate Investment, Competition, Tobin's Q, Zero Lower Bound.

JEL classifications: E2, E4, E5, L4.

1 Introduction

Since 2000, U.S. industries have become more concentrated and firms' profit margins have increased. Figure 1 shows the ratio of Corporate Profits[1] to Value Added for the U.S. Non-Financial Corporate sector, along with the weighted average change in 8-firm concentration ratio in manufacturing and non-manufacturing industries. Another important stylized fact – discussed below – is that business investment has been weak relative to measures of profitability, funding costs, and market values since

*We thank participants of the NBER Summer Institute for comments. The views expressed herein are those of the authors and should not be attributed to the IMF, its Executive Board, or its management.

†New York University, ggutierr@stern.nyu.edu

‡International Monetary Fund, jonescallum@gmail.com

§New York University, CEPR and NBER, tphilipp@stern.nyu.edu

[1] Corporate profits with inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj).

the early 2000s. Moreover, investment has been weak precisely in industries that have become more concentrated.

While these stylized facts are well established (Furman, 2015; Grullon, Larkin and Michaely, 2016; Gutiérrez and Philippon, 2017), their interpretation remains controversial. There is little agreement about the causes and consequences of these evolutions. For instance, Furman (2015) and CEA (2016) argue that the rise in concentration suggests "economic rents and barriers to competition", while Autor et al. (2017) argue almost exactly the opposite: that concentration reflects "a winner takes most feature" explained by the fact that "consumers have become more sensitive to price and quality due to greater product market competition." The evolution of profits and investment could also be explained by intangible capital deepening, as discussed in Crouzet and Eberly (2018).[2]

Several reasons explain why the literature has remained inconclusive. The first challenge is that entry, exit, concentration, investment, and markups are all jointly endogenous and it is difficult to find exogenous variations in any of these variables. The second challenge is that the macroeconomic implications of rising competition are difficult to analyze outside a fully specified model. As a result, both the empirical and the theoretical literature are limited. Empirically, little has been done to identify the causes of the trends in Figure 1. On the other hand, most theoretical models treat competition as a residual. They simply assume that markups have changed and study the implications without attempting to link them to independent measures of barriers to competition.

Our paper is a first attempt to address these issues. We propose a new approach to disentangle the various explanations by using a structural model together with micro-economic data. We build a fully specified macro model of the U.S. economy, featuring many industries and taking into account not only entry and investment, but also demand and interest rates.

The key identification issue is that entry and concentration are endogenous. To be concrete, consider an industry j where firms operate competitively under decreasing returns to scale. Suppose industry j receives the news at time t that the demand for its products will increase at some time $t + \tau$ in the future. There would be immediate entry of new firms in the industry. As a result, we would measure a decrease in concentration (or in Herfindahl indexes) followed and/or accompanied by an increase in investment. Anticipated demand (or productivity) shocks can thus explain why we see

[2] Trade and globalization can also explain some of the same facts (Feenstra and Weinstein, 2017). Foreign competition can lead to an increase in measured (domestic) concentration (e.g. textile industry), and a decoupling of firm value from the localization of investment. One could entertain other hypotheses – such as weak demand or credit constraints – but previous research has shown that they do not fit the facts. See Gutiérrez and Philippon (2017) for detailed discussions and references.

more investment in less concentrated industries even if it is not due to competition.

We make three contributions to the literature. Our first contribution is to use our model together with macro time series and panel data from firms and industries to address the identification issue. We specify a model with a rich set of demand and supply shocks, including shocks to investors' expectations, and we use the model's joint restrictions to identify the shocks. Using current output together with forward looking asset prices, our model can recover the shocks to expected demand across industries. We find that these shocks are large in the late 1990s, and, exactly as theory would predict, they explain variation in entry rates. Instead of being an empirical roadblock, however, these large shocks become a powerful way to estimate some important parameters of the model, such as the elasticity of entry to Tobin's Q.

Our main contribution is to link the structurally estimated shocks to measures of regulations and antitrust enforcement, thereby providing the first direct structural evidence that policy is (partly) responsible for decreasing competition in the U.S. economy. This requires many steps, as we explain below, but the broad intuition is relatively simple. Using Bayesian estimation methods, our model recovers a full panel of entry costs across time and industries. On the other hand, we use micro data to construct independent measures of entry regulations and M&A activities for the same set of industries. We show that the model-implied entry cost shocks track rather closely our empirical measures of entry regulations, even though they come from entirely different data sources and methodologies.

The final contribution of the paper is methodological but it turns out to be empirically important. We specify the likelihood function for the panel of data and we estimate the model while taking into account the zero lower bound (ZLB). We solve for the path of the economy using the solution method and approach of Jones (2018). We use a Kalman filter and information about expected duration of the ZLB to back out the other shocks that drive the model (including productivity, discount rate, risk premia). While this might seem like a separate issue, we show that, in fact, it is critical understand the behavior of the economy, for two reasons. The ZLB, by depressing the economy, has a significant impact on entry and therefore on concentration. If we did not properly model the ZLB, we would over-estimate the magnitude and impact of aggregate entry costs. In addition, because entry costs affect the natural rate of interest, the consequences of entry shocks are different with or without the ZLB.

To summarize, our main finding is that time-varying competition has had a significant impact on macro-economic dynamics over the past 30 years. For instance, absent the decrease in competition since 2003, consumption would be 5 to 10 percents higher by 2015 and the capital stock would have been 1 to 3 percent higher by 2015.

Literature Our approach introduces several new ways to examine the relationship between firm entry, competition, and the macroeconomy. A large empirical literature has looked at entry, concentration, and firms dynamics. Decker et al. (2015) argue that, whereas in the 1980's and 1990's declining dynamism was observed in selected sectors (notably retail), the decline was observed across all sectors in the 2000's, including the traditionally high-growth information technology sector. Furman (2015) shows that "the distribution of returns to capital has grown increasingly skewed and the high returns increasingly persistent" and argues that it "potentially reflects the rising influence of economic rents and barriers to competition."[3] CEA (2016) and Grullon et al. (2016) are the first papers to extensively document the broad increases in profits and concentration. Grullon et al. (2016) also show that firms in concentrating industries experience positive abnormal stock returns and more profitable M&A deals. Blonigen and Pierce (2016) find that M&As are associated with increases in average markups. Alexander and Eberly (2016), and Lee et al. (2016) present recent firm and industry level evidence on investment and Q. Dottling et al. (2017) find that concentration has increased in the U.S. while it has remained stable (or decreased) in Europe. Autor et al. (2017) study the link between concentration and the labor share. An important issue in the literature is the measurement of markups and excess profits. De Loecker and Eeckhout (2017) estimate markups using the ratio of sales to costs of goods sold. Over long horizons, however, it is difficult to separate excess profits from changes in the capital share. Barkai (2017), on the other hand, estimates directly the required return on capital and finds a significant increase in excess profits.

Our paper is also related to general equilibrium models with imperfect competition. Bilbiie et al. (2012) study how entry affects the propagation of business cycles in a standard RBC model with technology shocks. Eggertsson et al. (2018) take entry as exogenous and model a time-varying elasticity of substitution between intermediate goods to study the impact of time-varying market power on a number of broad macroeconomic trends. In our model, entry decisions are endogenous to the state of the economy, including future expectations of demand, and we connect entry costs to explicit measures of entry regulations.

[3] Furman (2015) also emphasizes emphasizes the weakness of corporate fixed investment and points out that low investment has coincided with high private returns to capital, implying an increase in the payout rate (dividends and shares buyback).

Following Eggertsson and Woodford (2003), a large and growing literature studies the consequences of a binding ZLB on the nominal rate of interest. The ZLB has been proposed as an explanation for the slow recovery of most major economies following the financial crisis of 2008-2009 (Summers, 2013). Eggertsson et al. (2019) propose a model of secular stagnation, including a study of the role of demographic changes. Swanson and Williams (2014) study the impact on long rates. Most studies of the liquidity trap are based on simple New-Keynesian models that abstract from capital accumulation (see Fernández-Villaverde et al. 2015 for the exact properties of the New Keynesian model around the ZLB). Capital accumulation complicates matters, however, as consumption and investment can move in opposite directions.

Section 2 presents the relevant facts about the U.S. economy in recent years. Section 3 presents our benchmark model. We start from a standard DSGE model in which we allow for the possibility that the zero lower bound constraint on short term nominal rates binds.

2 Two Facts About Profits and Investment

This section shows why it is critical to understand the dynamics of investment in concentrating industries.[4]

Fact 1: Investment is Low Relative to Profits and Q. The first stylized fact is that business investment has been weak relative to measures of profitability, funding costs, and market values since the early 2000s. The top chart in Figure 2 shows the ratio of aggregate net investment and net repurchases to net operating surplus for the non financial corporate sector, from 1960 to 2015. As shown, investment as a share of operating surplus has fallen, while buybacks have risen. The bottom chart shows the residuals (by year and cumulative) of a regression of net investment on (lagged) Q from 1990 to 2001, illustrating that investment has been low relative to Q since the early 2000's. By 2015, the cumulative under-investment is large at around 10% of capital.

Fact 2: The Rise in Profits and Lack of Investment Comes from Concentrating Industries. Grullon et al. (2016) show that profits increased in concentrating industries. Figure 3 shows that the capital gap is coming from concentrating industries. The solid (dotted) line plots the implied capital gap relative to Q for the top (bottom) 10 concentrating industries. For each group, the capital gap

[4]See Appendix A.2 for additional details on the construction of these Figures and Tables.

is calculated based on the cumulative residuals of separate industry-level regressions of net industry investment from the BEA on our measure of (lagged) industry Q from Compustat.

3 Model

Motivated by these facts, we use a model with capital accumulation, nominal rigidities, and time-varying competition with firm entry. We organize firms into industries and, for simplicity, separate them into capital producers – who lend their capital stock – and good producers – who hire capital and labor to produce goods and services. We use data at the industry-level on concentration and profitability to estimate the elasticity of firm entry to changes in Q. We then use those estimates to understand the aggregate consequences of changes in entry costs.

We use a standard nested CES demand system. The final good is a composite of industry-level outputs aggregated by a perfectly competitive final goods firm:

$$Y_t = \left[\int_0^1 (D_{j,t} Y_{j,t})^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}j \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where σ is the elasticity of demand across industry-level goods, and $D_{j,t}$ is an industry-level demand shifter. The price index for Y_t is P_t, defined as

$$P_t = \left(\int_0^1 P_{j,t}^{1-\sigma} \mathrm{d}j \right)^{\frac{1}{1-\sigma}}, \tag{2}$$

where $P_{j,t}$ is the price index of industry j. There are many variables and indexes in the model. As a rule, we define real variables (i.e., scaled by the GDP deflator P_t) unless there are nominal rigidities. So, for instance, $R^k_{j,t}$ is the real rental rate of capital in industry j, but W_t is be the nominal wage and $p_{i,j,t}$ is the nominal price set by firm i in industry j.

3.1 Capital Producers

A capital-producing firm in industry j accumulates capital K_j to maximize its market value, taking as given the economy's (real) pricing kernel Λ_t. Management chooses employment and investment to maximize firm value. Let $V^k_{j,t}$ denote the cum-dividend value (at the beginning of time t, before dividends are paid) of a capital-producing firm:

$$V_{j,t}^{k}=\mathbb{E}_{t}\sum_{i=0}^{\infty}\Lambda_{t+i}\mathrm{Div}_{j,t+i}, \tag{3}$$

where $\mathrm{Div}_{j,t}$ are the distributions to the firm's owners. Capital in industry j accumulates as

$$K_{j,t+1}=(1-\delta)\,K_{j,t}+I_{j,t}. \tag{4}$$

Let $R_{j,t}^{k}$ be the real rental rate on capital in the industry, $I_{j,t}$ gross investment, and $P_{j,t}^{k}$ be the (real) price of investment goods. Investment is subject to convex adjustment costs à la Lucas and Prescott (1971) and we ignore taxes so that dividends are

$$\mathrm{Div}_{j,t}=R_{j,t}^{k}K_{j,t}-P_{j,t}^{k}I_{j,t}-\frac{\phi_{k}}{2}P_{j,t}^{k}K_{j,t}\left(\frac{I_{j,t}}{K_{j,t}}-\delta\right)^{2}. \tag{5}$$

The firm's problem is to maximize (3) subject to (4) and (5). We can write the firm's objective as the dynamic programming problem

$$V_{j,t}^{k}\left(K_{j,t}\right)=\max_{I_{j,t}}\mathrm{Div}_{j,t}+\mathbb{E}_{t}\left[\Lambda_{t+1}V_{j,t+1}^{k}\left(K_{j,t+1}\right)\right]. \tag{6}$$

Given our capital adjustment cost assumptions, the value function is homogeneous in capital $K_{j,t}$. We can then define $\mathcal{V}_{j,t}^{k}\equiv\frac{V_{j,t}^{k}}{K_{j,t}}$ and net investment $x_{j,t}\equiv\frac{I_{j,t}}{K_{j,t}}-\delta=\frac{K_{j,t+1}-K_{j,t}}{K_{j,t}}$ and write the problem of the firm as

$$\mathcal{V}_{j,t}^{k}=\max_{x_{j,t}}\ \left[R_{j,t}^{k}-P_{j,t}^{k}\left(x_{j,t}+\delta\right)-\frac{\varphi_{k}}{2}P_{j,t}^{k}x_{j,t}^{2}+\left(1+x_{j,t}\right)\mathbb{E}_{t}\left[\Lambda_{t+1}\mathcal{V}_{j,t+1}^{k}\right]\right]. \tag{7}$$

The solution of this problem is the Q-investment equation,

$$x_{j,t}=\frac{1}{\phi_{k}}\left(Q_{j,t}^{k}-1\right), \tag{8}$$

where $Q_{j,t}^{k}$ is Tobin's Q, defined as

$$Q_{j,t}^{k}\equiv\frac{\mathbb{E}_{t}\left[\Lambda_{t+1}\mathcal{V}_{j,t+1}^{k}\right]}{P_{j,t}^{k}}=\frac{\mathbb{E}_{t}\left[\Lambda_{t+1}V_{j,t+1}^{k}\right]}{P_{j,t}^{k}K_{j,t+1}}, \tag{9}$$

which is the market value of the firm divided by the replacement cost of capital, all measured at the end of the period. We index it by k to distinguish it from the total industry-level Q which includes the rents of the final producers discussed below. Tobin's Q satisfies the recursive equation

$$Q_{j,t}^{k}=\mathbb{E}_t\left[\frac{\Lambda_{t+1}}{P_{j,t}^{k}}\left(R_{j,t+1}^{k}+P_{j,t+1}^{k}\left(\left(1+x_{j,t+1}\right)Q_{j,t+1}^{k}-x_{j,t+1}-\delta-\frac{\phi_k}{2}x_{j,t+1}^{2}\right)\right)\right], \tag{10}$$

which, given (8), can be written as

$$Q_{j,t}^{k}=\mathbb{E}_t\left[\frac{\Lambda_{t+1}}{P_{j,t}^{k}}\left(R_{j,t+1}^{k}+P_{j,t+1}^{k}\left(Q_{j,t+1}^{k}-\delta+\frac{1}{2\phi_k}\left(Q_{j,t+1}^{k}-1\right)^{2}\right)\right)\right]. \tag{11}$$

In the logic of the Q-theory of investment, $Q_{j,t}^{k}$ is the discounted value of operating returns in industry j, $R_{j,t+1}^{k}$, plus future $Q_{j,t}^{k}$ net of depreciation, plus the option value of investing more when $Q_{j,t}^{k}$ is high, and less when $Q_{j,t}^{k}$ is low.

3.2 Goods Producers

The goods-producing firms in industry j hire capital and labor for production and make pricing decisions. The number of firms in an industry in our model is time-varying. Firms pay an entry cost to become active producers in the subsequent period, with the price of entry increasing in the number of entrants.

3.2.1 Price Setting

Each industry j is populated by firms indexed by i who face pricing and production decisions. They face the industry demand curve

$$Y_{j,t}=D_{j,t}\left(\frac{P_{j,t}}{P_t}\right)^{-\sigma}Y_t. \tag{12}$$

The firms' output is aggregated into an industry output

$$Y_{j,t}=\left(\int_0^{N_{j,t}}y_{i,j,t}^{\frac{\epsilon_j-1}{\epsilon_j}}\,\mathrm{d}i\right)^{\frac{\epsilon_j}{\epsilon_j-1}}. \tag{13}$$

where $N_{j,t}$ is the number of firms in industry j active (producing) at time period t and ϵ_j is the elasticity of substitution across firms within the industry. The industry price index is an aggregate of firm level price choices:

$$P_{j,t} = \left(\int_0^{N_{j,t}} p_{i,j,t}^{1-\epsilon_j} \mathrm{d}i \right)^{\frac{1}{1-\epsilon_j}}. \tag{14}$$

Firm i has access to a Cobb-Douglas production function with stationary TFP shocks $A_{j,t}$, and takes economy-wide wages W_t/P_t and the rental rate $R_{j,t}^k$ as given when they minimize average costs:

$$\min_{\ell_{i,j,t}, k_{i,j,t}} \frac{W_t}{P_t} \ell_{i,j,t} + R_{j,t}^k k_{i,j,t}, \tag{15}$$

subject to the production function

$$y_{i,j,t} = A_{j,t} k_{i,j,t}^{\alpha} \ell_{i,j,t}^{1-\alpha}. \tag{16}$$

The marginal cost depends on the real wage (there are no frictions in the labor market) and on the industry specific rental rate (capital is subject to adjustment costs). Firms in industry j face the same factor prices, and so have identical marginal costs, denoted by $\chi_{j,t}$:

$$\chi_{j,t} = \frac{1}{A_{j,t}} \left(\frac{R_{j,t}^k}{\alpha} \right)^{\alpha} \left(\frac{W_t/P_t}{1-\alpha} \right)^{1-\alpha}. \tag{17}$$

Factor choices in the firm's problem imply the choice of capital and labor are simply $k_{i,j,t} = \alpha \frac{\chi_{j,t}}{R_{j,t}^k} y_{i,j,t}$ and $\ell_{i,j,t} = (1-\alpha) \frac{\chi_{j,t}}{W_t/P_t} y_{i,j,t}$. All goods-producing firms choose the same capital labor ratio $\frac{\ell_{i,j,t}}{k_{i,j,t}} = \left(\frac{1-\alpha}{\alpha}\right) \frac{R_{j,t}^k}{W_t/P_t}$.

In the full model used for estimation we assume that firms face some nominal rigidities in order to obtain well-behaved industry Phillips curves.[5] Since these small rigidities have second order effects on values and productivities, we simplify the exposition by presenting the flexible price equations. With flexible prices, firms set a fixed markup over marginal cost $p_{i,j,t} = \mu_j \chi_{j,t}$, where $\mu_j = \frac{\epsilon_j}{\epsilon_j - 1}$. The flexible industry-level price (14) becomes $P_{j,t} = \mu_j \chi_{j,t} N_{j,t}^{\frac{1}{1-\epsilon_j}}$. Since all firms have the same output, we can write

$$Y_{j,t} = \left(\int_0^{N_{j,t}} y_{i,j,t}^{\frac{\epsilon_j - 1}{\epsilon_j}} \mathrm{d}i \right)^{\frac{\epsilon_j}{\epsilon_j - 1}} = y_{j,t} \left(N_{j,t} \right)^{\frac{\epsilon_j}{\epsilon_j - 1}}. \tag{18}$$

[5]Formally, we assume that firms set prices à la Calvo (with indexation on average inflation in sector j) so that the reset price at time t, $p_{i,j,t}^*$, solves

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} \vartheta_p^k \Lambda_{t+k} y_{i,j,t+k} \left(1 - \epsilon_j + \epsilon_j \frac{P_{j,t+k}}{p_{i,j,t}^*} \frac{P_{t+k}}{P_{j,t+k}} \chi_{j,t+k} \right) \right] = 0.$$

Indexation keeps the dispersion of prices small. In addition, we estimate relatively small nominal rigidities, so the impact of these rigidities on productivity (output) and value (Tobin's Q) are negligible.

where, with some abuse of notation, we denote by $y_{j,t}$ the average firm output in industry j. We see here is impact of product variety on productivity. The economy's flexible price index from (2) can be written as P_t.

3.2.2 Firm Entry

We model firm entry in the goods-producing sector as follows. The number of firms in industry j evolves according to

$$N_{j,t+1} = (1 - \delta_n) N_{j,t} + n_{j,t}. \tag{19}$$

Each active firms disappears with probability δ_n, while $n_{j,t}$ is the number of new entrants that become active in period $t + 1$. Entry requires a fixed input κ_t produced by a competitive industry with a convex cost function, so that the input price is

$$p^e_{j,t} = (\kappa_t n_{j,t})^{\phi_n} \,. \tag{20}$$

Free entry then requires that

$$p^e_{j,t} \kappa_t \geq \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}, \tag{21}$$

where $V_{j,t} = (1 - \chi_{j,t}) y_{j,t} + (1 - \delta_n) \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}$ is the value of the goods-producing firm and $y_{j,t}$ is average output as explained earlier. Equation (21) holds with equality as long as $n_{j,t} > 0$, which is the case in our simulations.

Finally, an industry's total Q combines the rents of capital and goods producers, all measured at the end of the period

$$Q_{j,t} = Q^k_{j,t} + \frac{(1 - \delta_n) \mathbb{E}_t \left[\Lambda_{t+1} V_{j,t+1} \right]}{P^k_t K_{j,t+1}}. \tag{22}$$

The elasticity of the number of entrants $n_{j,t}$ to $Q_{j,t}$ is therefore parameterized by ϕ_n. The cross-industry relationships between concentration, profits, and output will be key to determining this sensitivity, which is important for quantifying the aggregate effects of entry shocks.

3.3 Households

We next introduce a standard household sector and wage setting mechanism. Households maximize lifetime utility

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\gamma}}{1-\gamma} - \frac{\ell_t^{1+\varphi}}{1+\varphi} \right) \right], \tag{23}$$

subject to the budget constraint

$$S_t + P_t C_t \leq \tilde{R}_t S_{t-1} + W_t \ell_t, \tag{24}$$

where W_t is the nominal wage and $\tilde{R}_t$ is the (random) nominal gross return on savings from time $t-1$ to time t. The household's real pricing kernel between periods t and $t+j$ is

$$\Lambda_{t+j} = \beta^j \left(\frac{C_t}{C_{t+j}} \right)^{\gamma}. \tag{25}$$

By definition of the pricing kernel, nominal asset returns must satisfy

$$\mathbb{E}_t \left[\Lambda_{t+1} \frac{P_t}{P_{t+1}} \tilde{R}_{t+1} \right] = 1. \tag{26}$$

Wage setting Wage setting takes place as in the standard New Keynesian model (see Gali, 2008). The wage reset at time t, W_t^*, solves

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} (\beta \vartheta_w)^k \, \ell_{l,t+k} C_{t+k}^{-\gamma} \left(\frac{1-\epsilon_w}{P_{t+k}} + \epsilon_w \frac{\mathtt{MRS}_{t+k}}{W_t^*} \right) \right] = 0, \tag{27}$$

where ϵ_w is the elasticity of substitution between labor varieties and where we define the marginal rate of substitution as

$$\mathtt{MRS}_{l,t+k} \equiv \ell_{l,t+k}^{\varphi} C_{t+k}^{\gamma}. \tag{28}$$

3.4 Monetary Policy

Finally, to close the model, we specify a policy rule for the central bank, taking into account the zero lower bound on nominal interest rates. We assume that monetary policy follows a Taylor rule for the nominal interest rate

$$\tilde{r}_t^* = -\log(\beta) + \phi_i \tilde{r}_{t-1}^* + (1-\phi_i) \left(\phi_p \pi_t^p + \phi_y \left(\ln Y_t - \ln Y_t^F \right) \right), \tag{29}$$

where π_t^p is price-level inflation, Y_t^F is the flexible price level of output, and where the actual (log) short rate is constrained by the zero lower bound

$$\tilde{r}_t = \max(0; \tilde{r}_t^*). \tag{30}$$

At the zero lower bound, we allow for forward guidance as an extension of the zero lower bound duration beyond that implied by fundamentals and the shocks. We discipline the durations by using the durations observed, as discussed in the estimation section below.

3.5 Shocks

We model the following shocks (where lowercase letters denote variables in logs):

- Industry-level demand shifter $d_{j,t} = \log D_{j,t}$:

$$d_{j,t} = (1 - \tilde{\rho}_d)d_j + \tilde{\rho}_d d_{j,t-1} + \tilde{\sigma}_d \epsilon^d_{j,t}. \tag{31}$$

  We estimate transitory shocks to $d_{j,t}$, or $\epsilon^d_{j,t}$, to help account for variation in relative industry output over time. We also estimate shocks to *beliefs* about d_j, the steady-state value of demand, which can differ from fundamentals. In our baseline specification, we will estimate changes to steady-state beliefs between 1995Q1 and 1999Q4. This specification is chosen to account for excess entry observed in a number of industries before 2000.[6]

- A productivity shock to industry-level output, for $a_{j,t} = \log A_{j,t} = \log A_j + \zeta^a_{j,t} + \zeta^a_t$, where

$$\zeta^a_{j,t} = \tilde{\rho}_a \zeta^a_{j,t-1} + \tilde{\sigma}_a \epsilon^a_{j,t} \tag{32}$$

$$\zeta^a_t = \rho_a \zeta^a_{t-1} + \sigma_a \epsilon^a_t. \tag{33}$$

  There are, therefore, industry-specific and aggregate shocks to productivity.

- A shock to the valuation of corporate assets for both capital-producing and goods-producing

[6] The presence of noisy entry is documented in several papers. Doms (2004), for example, studies IT investment and firm entry during the 1990s. He concludes that a "reason for the high growth rates in IT investment was that expectations were too high, especially in two sectors of the economy, telecommunications services and the dot-com sector," where dot-com covers a wide range of traditional sectors, from retail trade to business services. See also Hogendorn (2011). One explanation for noisy entry is potential variations in the willingness of investors (venture capitalists, or market participants in general) to fund risky ventures. This is particularly important during the 1990s given the large inflows into Venture Capital (VC). According to the National Venture Capital Association, annual VC commitments surged during the bubble period, growing from about \$10 billion in 1995 to more than \$100 billion in 2000. They then receded to about \$30 billion per year for the next decade (NVCA (2010)). According to Gompers and Lerner (2001), about 60 percent of VC funding in 1999 went to information technology industries, especially communications and networking, software, and information services. About 10 percent went into life sciences and medical companies, and the rest is spread over all other types of companies. Clearly, not all entry is funded by VC firms, so this can only explain a portion of the variation in entry rates, but the wide dispersion, and strong industry focus highlights the differential impact of the dot-com bubble across industries. Another explanation is the presence of large stock market variations across industries, as documented by Anderson et al. (2010). These extreme valuations may translate into excess investment and excess entry, especially because firm entry increases precisely during periods of high-growth such as the late 1990's.

firms

$$q^k_{j,t} = \mathbb{E}_t \left[\lambda_{t+1} + \log \left(r^k_{j,t+1} + q^k_{j,t+1} + 1 - \delta + \frac{1}{2\phi_k} \left(q^k_{j,t+1} \right)^2 \right) \right] + \zeta^q_{j,t} + \zeta^q_t \tag{34}$$

$$q^\epsilon_{j,t} = \mathbb{E}_t \left[\lambda_{t+1} + v^\epsilon_{j,t+1} - k_{j,t+1} \right] + \zeta^q_{j,t} + \zeta^q_t, \tag{35}$$

where the industry-level shock $\zeta^q_{j,t}$ and the aggregate-level shock ζ^q_t are given by

$$\zeta^q_{j,t} = \tilde{\rho}_q \zeta^q_{j,t-1} + \tilde{\sigma}_q \epsilon^q_{j,t} \tag{36}$$

$$\zeta^q_t = \rho_q \zeta^q_{t-1} + \sigma_q \epsilon^q_t. \tag{37}$$

The valuation shock is a *risk premium* shock that applies to corporate (risky) assets, which will help us account for time varying-risk aversion and expected returns. In reduced-form, this shock has similar implications as the marginal efficiency of investment shocks studied by Justiniano et al. (2011).

- Aggregate and industry-specific shocks to the entry cost

$$\kappa_{j,t} = \kappa + \zeta^\kappa_{j,t} + \zeta^\kappa_t, \tag{38}$$

where the industry and aggregate-level shocks are autoregressive processes

$$\zeta^\kappa_{j,t} = \tilde{\rho}_\kappa \zeta^\kappa_{j,t-1} + \tilde{\sigma}_\kappa \epsilon^\kappa_{j,t} \tag{39}$$

$$\zeta^\kappa_t = \rho_\kappa \zeta^\kappa_{t-1} + \sigma_\kappa \epsilon^\kappa_t. \tag{40}$$

- We also include aggregate and industry-specific shocks to the linearized inflation equation

$$\zeta^e_{j,t} = \tilde{\rho}_e \zeta^e_{j,t-1} + \tilde{\sigma}_e \epsilon^e_{j,t} \tag{41}$$

$$\zeta^e_t = \rho_\kappa \zeta^e_{t-1} + \sigma_e \epsilon^e_t. \tag{42}$$

These shocks will help us account for the observed variation in prices at the industry and aggregate level.

In addition to the aggregate shocks to productivity, valuation of corporate assets, entry costs, and economy-wide inflation, we include the following shocks at the aggregate level. These shocks will help us account for the aggregate data.

- A discount rate shock to the pricing kernel, which helps match the sharp drop in risk free rates during the Great Recession, as is standard in the New Keynesian literature

$$\lambda_{t+1} = \log \beta - \gamma \left(c_{t+1} - c_t\right) + \zeta_t^b \tag{43}$$

$$\zeta_t^b = \rho_b \zeta_{t-1}^b + \sigma_b \epsilon_t^b. \tag{44}$$

- A shock to the monetary policy rule

$$\tilde{r}_t^* = -\log\left(\beta\right) + \phi_i \tilde{r}_{t-1}^* + \left(1 - \phi_i\right)\left(\phi_p \pi_t^p + \phi_y \left(\ln Y_t - \ln Y_t^F\right)\right) + \sigma_i \epsilon_t^i. \tag{45}$$

4 Estimation

We next discuss the parameterization of the model for the quantitative analysis. We first calibrate a set of parameters to those commonly used in the literature and to moments in the data. We then estimate with Bayesian methods a small set of key structural parameters, beliefs about demand, and the persistence and size of transitory shocks.

The estimation is conducted in two stages. In the first stage, the industry-level data is used to estimate σ and ϕ_n, along with the parameters of the industry-level shock processes. In the second stage, the estimated value of ϕ_n is used in an aggregated version of the model with a single sector, and the parameters of the aggregate-level shock processes are estimated. We then use the estimated aggregate model to conduct our aggregate experiments on the role of firm entry.

4.1 Calibrated Parameters

Table 1 presents the assigned and calibrated parameters for our quarterly model. These estimates are based on 43 industries that cover the U.S. Business sector.[7] We set δ_n, the exogenous firm exit rate, to 0.09/4 to match the average annual exit rate of Compustat firms.[8] We calibrate the quarterly capital

[7] Investment and output data are available for 63 granular industry groupings from the BEA. We omit 7 industries in the Finance, Insurance and Real Estate sector. We also omit the 'Management of companies and enterprises' industry because no data is available in Compustat for it. We then group some of the remaining industries due to missing data at the most granular-level (Hospitals and Nursing and residential care facilities), or to ensure that all groupings have material investment; good Compustat coverage; and reasonably stable investment and concentration time series.

[8] We use Compustat firms to focus on the exit of large firms.

adjustment cost ϕ_k to a value of 20, in line with a regression across industries of net investment on Tobin's Q, with a full set of time and industry fixed effects. Next, we calibrate the within-industry, across-firm elasticities of substitution, ϵ_j, parameters to match the gross operating surplus to output ratio in 1993 from the BEA industry series.[9] Most values are centered around 5, the standard calibration in New Keynesian models, while some industries have higher elasticities of substitution, which reflect relatively low and persistent profit levels in those industries.[10]

In the second stage of the estimation with a single intermediate-goods sector, we set the elasticity of substitution across varieties to $\epsilon = 5$, which is around the average of our calibrated ϵ_j parameters across industries, and which is in line with a standard calibration of the elasticity of substitution in the New Keynesian literature, implying a steady-state markup of 25%. We also calibrate the parameters of the monetary policy rule to those estimated by Justiniano and Primiceri (2008), with a weight on the interest rate smoothing parameter ϕ_r of 0.86, a weight on deviations of inflation from target of ϕ_p of 1.71, and a weight on deviations of output from its flexible price level ϕ_y of 0.05.

4.2 Estimated Parameters

With industry-level data, we estimate σ, ϕ_n, and the persistence and variance of the industry-level shocks. We also estimate beliefs d_j about the steady-state level of demand in industry j, which all agents are assumed to hold between 1995Q1 and 1999Q4, and which we assume revert to their true value of $d_j = 0$ in 2000Q1. With aggregate-level data, we estimate the persistence and variance of aggregate shocks.

4.3 Data

We use cross-sectional data in our identification, based on heterogeneity across industries (and firms). At the industry level, we use annual data on concentration ratios, Q, nominal output, capital, and prices, from 1989 to 2015.[11]

- We measure concentration for BEA segments using the data of Gutiérrez and Philippon (2017) from Compustat. In particular, we measure the concentration ratio as the share of sales by the

[9] The model's implied steady-state gross operating surplus to output ratio changes as σ changes. In the estimation we recalibrate the values of ϵ_j accordingly. Figure A.2 in the Appendix plots the distribution of ϵ_j across industries in our baseline calibration.

[10] For most industries, the gross operating surplus to output ratios are stable and do not change much over time, as we show in the Appendix.

[11] The Appendix provides a complete description of the data used.

top 8 firms in the industry (concentration ratio).[12] To account for global competition, we correct the concentration ratio for imports using data from Pierce and Schott (2012). In the model, all firms are identical, so that the Herfindahl index is $\int \left({}^{y_{i,j,t}}/_{Y_{j,t}}\right)^2 \mathrm{d}i = \int \left({}^{y_{i,j,t}}/_{N_{j,t} y_{j,t}}\right)^2 \mathrm{d}i = {}^1/_{N_{j,t}}$. We therefore match the concentration ratio we measure in the data to ${}^1/_{N_{j,t}}$ in the model.

- We measure industry Q as the ratio of market value to total assets across all firms in Compustat that belong to a given BEA industry.[13] In our baseline, we match the observed values of Q to the Q of goods-producers.[14]

- We measure nominal output and and prices at the industry-level using the BEA's GDP-By-Industry accounts.

- We measure investment and capital stocks at the industry-level using the BEA's Fixed Assets Tables.

To compare the model and the data, we express the industry-level data series relative to their respective aggregate series, by subtracting a full set of time effects, one for each year and each variable. We also subtract an industry-specific fixed effect. The resulting series for each industry are plotted in the Appendix.

At the aggregate level, our data is quarterly from 1989Q1 to 2015Q1, and includes the Fed Funds rate, the change in real consumption per capita, the net investment rate, inflation, and employment. We also link observed changes in the aggregate concentration ratio to changes in the model's aggregate Herfindahl index. To discipline the expected durations of the zero lower bound between 2009Q1 and 2015Q1, we use data from the New York Federal Reserve Survey of Primary Dealers, following Kulish et al. (2017). The Appendix describes and plots the aggregate data that we use.

4.4 Solution Method

We use the *relative* variation across industries to identify the key parameters of our model that are critical for governing the dynamics of firm entry. Using industry-level variation for our identification builds on Jones, Midrigan and Philippon (2018), and exploits the structure of the model to overcome

[12]We have validated that Compustat-based concentration ratios (adjusted for the share of Compustat sales) exhibit similar behavior as the Census. The two series exhibit a 65 to 70% correlation in levels and 40 to 50% in 5-year changes, while the aggregate trend is also similar.

[13]Gutiérrez and Philippon (2017) compare alternate measures of Q used in the literature and conclude that market-to-book is the most robust and stable definition

[14]We explore robustness to matching Q in the data to the aggregate sector level Q, which combines both the rents of the goods-producers and the capital-producers. We discuss these robustness exercises below.

two key challenges with respect to the approximation of our model. The first challenge is to model time-varying beliefs about the steady-state of industry-level demand that differs from fundamentals, for each industry. The second challenge is to simultaneously account for the nonlinearities caused by the zero lower bound. In this section, we discuss each challenge in turn. In the next section, we discuss how we use our approximation below to form the likelihood function for estimation.

Solution Method for Beliefs We first discuss the linearized solution under time-varying beliefs for a single industry denoted by j, abstracting from industry j's dependence on aggregate variables. We follow Kulish and Gibbs (2017) in specifying two regimes: one under the industry's true parameters, and another where beliefs about demand differ from the truth. Denote the true demand regime which is driving the observables as

$$\mathbf{A}\mathbf{x}_t^j = \mathbf{C} + \mathbf{B}\mathbf{x}_{t-1}^j + \mathbf{D}\mathbb{E}_t\mathbf{x}_{t+1}^j + \mathbf{F}\epsilon_t^j, \tag{46}$$

where $\mathbf{x}_t^j$ is the vector of state variables for an industry j and ϵ_t^j collects the shocks for industry j. However, suppose that agents in the model instead believe that an alternative demand regime is true, believing that the industry's law of motion is driven by the regime denoted by the $*$ matrices

$$\mathbf{A}^*\mathbf{x}_t^j = \mathbf{C}^* + \mathbf{B}^*\mathbf{x}_{t-1}^j + \mathbf{D}^*\mathbb{E}_t\mathbf{x}_{t+1}^j + \mathbf{F}^*\epsilon_t^j. \tag{47}$$

Our goal is to construct the reduced-form VAR approximation for industry j of the form

$$\mathbf{x}_t^j = \mathbf{J}_t + \mathbf{Q}_t\mathbf{x}_{t-1}^j + \mathbf{G}_t\epsilon_t^j. \tag{48}$$

In periods when beliefs $\mathbb{E}_t\mathbf{x}_{t+1}^j$ accord with regime (46), the solution is the standard time-invariant solution

$$\mathbf{x}_t^j = \mathbf{J} + \mathbf{Q}\mathbf{x}_{t-1}^j + \mathbf{G}\epsilon_t^j. \tag{49}$$

Instead, in periods when beliefs $\mathbb{E}_t\mathbf{x}_{t+1}^j$ are formed with (47) then $\mathbb{E}_t\mathbf{x}_{t+1}^j = \mathbf{J}^* + \mathbf{Q}^*\mathbf{x}_t^j$, where $\mathbf{J}^*$ and $\mathbf{Q}^*$ are the matrices of the reduced form solution corresponding to the system (47). Substituting these beliefs $\mathbb{E}_t \mathbf{x}^j_{t+1}$ into (46) and rearranging gives

$$\tilde{\mathbf{Q}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} \mathbf{B} \tag{50}$$

$$\tilde{\mathbf{G}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} \mathbf{F} \tag{51}$$

$$\tilde{\mathbf{J}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} [\mathbf{C} + \mathbf{D}\mathbf{J}^*] \tag{52}$$

For our time-varying representation (48), we therefore set $\mathbf{Q}_t = \mathbf{Q}$, $\mathbf{G}_t = \mathbf{G}$, and $\mathbf{J}_t = \mathbf{J}$ in periods when beliefs align with the truth, and $\mathbf{Q}_t = \tilde{\mathbf{Q}}$, $\mathbf{G}_t = \tilde{\mathbf{G}}$, and $\mathbf{J}_t = \tilde{\mathbf{J}}$ in periods when beliefs differ from the truth.

Zero Lower Bound Our second computational challenge is to approximate the dynamics of our model where the policy rate is subject to the zero lower bound. We do so following the approach of Guerrieri and Iacoviello (2015) and Jones (2017). The logic of the solution follows the time-varying approximation (48) that we use for estimating demand beliefs. We define two additional regimes, one for when the zero lower bound does not bind, and one for when the zero lower bound binds. At each point in time the zero lower bound is observed, we assume that agents believe no shocks will occur in the future and iterate backwards through our model's equilibrium conditions from the date that the zero lower bound is conjectured to stop binding. We then iterate on the periods that the interest rate is conjectured to be in effect until it converges, after which the solution is that in (48).

4.5 The Likelihood Function

The direct approach to estimating the parameters of the model and demand beliefs would be to form the likelihood function using the solution (48) and the industry and aggregate data together. However, the nonlinearities induced by the zero lower bound together with the large number of industries makes this approach computationally infeasible.

As a result, we follow Jones, Midrigan and Philippon (2018) and construct the likelihood function differently and exploit the relative variation across industry outcomes for identification. This approach allows us to separate the likelihood into an industry-level component and an aggregate component and conduct the estimation in two stages.

Let $\mathbf{x}^j_t$ denote the vector of variables for each industry j, expressed in log-deviations from the steady state. Under a piece-wise linear approximation and an assumption that aggregate shocks propagate to each industry in the same way we can write the evolution of $\mathbf{x}_t^j$ as the sum of two components:

$$\mathbf{x}_t^j = \mathbf{J} + \mathbf{Q}\mathbf{x}_{t-1}^j + \mathbf{G}\epsilon_t^j + \mathbf{J}_t^a + \mathbf{Q}_t^a\mathbf{x}_{t-1}^* + \mathbf{G}_t^a\epsilon_t^*. \tag{53}$$

Here, the first set of matrices, $\mathbf{J}$, $\mathbf{Q}$ and $\mathbf{G}$, account for how an industry's variables depend on its own state variables and industry-specific shocks ϵ_t^j, while the vector $\mathbf{x}_t^*$ collects the aggregate variables and ϵ_t^* collects the aggregate shocks, and the matrices $\mathbf{J}_t^a$, $\mathbf{Q}_t^a$ and $\mathbf{G}_t^a$ express how the industries' variables depend on the aggregate variables, with the aggregate variables evolving according to:

$$\mathbf{x}_t^* = \mathbf{J}_t^* + \mathbf{Q}_t^*\mathbf{x}_{t-1}^* + \mathbf{G}_t^*\epsilon_t^* \tag{54}$$

The matrices multiplying the aggregate variables and shocks are time-varying because of the nonlinearities caused by the zero lower bound. In contrast, the matrix of coefficients $\mathbf{J}$, $\mathbf{Q}$ and $\mathbf{G}$ multiplying the industry-level variables is time-invariant.

Intuitively, under (53), for an industry j, aggregate shocks and the zero lower bound do not change the response of firms in that industry to its own history of idiosyncratic shocks. Under this, letting $\mathbf{x}_t = \int \mathbf{x}_t^j \mathrm{d}j$ denote the economy-wide average of the industry-level variables, the deviation of industry-level variables from their economy-wide averages,

$$\hat{\mathbf{x}}_t^j = \mathbf{x}_t^j - \mathbf{x}_t, \tag{55}$$

can be written as a time-invariant function of industry-level variables alone:

$$\hat{\mathbf{x}}_t^j = \mathbf{J} + \mathbf{Q}\hat{\mathbf{x}}_{t-1}^j + \mathbf{G}\epsilon_t^j, \tag{56}$$

where we use the assumption $\int \epsilon_t^j \mathrm{d}j = 0$, that industry-level shocks have zero mean in the aggregate. We then use the representation in (54) and (56) to estimate the model using industry-level and aggregate U.S. data, separately. Because the industry-level outcomes are independent of each other, the likelihood contribution of industry-level data as a whole is the sum of each industry's likelihood contribution. We then use standard Bayesian methods to characterize the posterior distribution of the model's parameters.

4.6 Estimates

Table 2 presents moments of the prior and posterior distributions of the estimated parameters, for both the industry and aggregate-level parameters.

Industry Estimates Panel A shows the estimates of σ and ϕ_n, and Panel B shows moments of the posterior distributions of the persistence and standard errors of the industry specific shocks. We choose wide priors for the parameters. The value of σ is estimated to be around 0.4, suggesting that the industry-level outputs are complementary, which is reasonable for broad classes of goods, and consistent with the trade literature. The value of ϕ_n is around 1.5, with a 10th and 90th percentile of 1.1 and 2.3, respectively. The implications of these estimates for the speed of firm entry are discussed in the next section. The persistence of entry shocks is low, being centered around 0.1. The persistence of demand shocks is high, close to 1, while the persistence of the technology shocks is around 0.9.

The estimates of beliefs about demand that are held between 1995 and 2000 are plotted in Figure 4. Agents in the model hold beliefs about steady-state demand D_j during this period, when in truth, the steady-state value of demand for all industries is $D_j = 1$. We choose a diffuse prior for each estimated D_j which is an equal mixture of an inverse gamma distribution with a mode of 1 and a uniform distribution between 0 and 100. This prior has a 10th percentile around 1, a mode slightly above 1, and a 90th percentile around 80. We assume that from 2000 on, beliefs revert and align with their true assumed values.

Most estimates of $D_j = \log d_j$ are around their fundamental value of $d_j = 0$. Some industries are estimated to have low expected demand; for example, rail transport has an estimated expected steady-state demand of around -0.5. In addition, some durable manufacturing industries are estimated to have low beliefs about demand, such as durable non-metal and durable miscellaneous manufacturing, which have estimated steady-state demands of around -0.3. Agriculture, waste management, and wholesale trade are also estimated to have comparatively low beliefs about steady-state demand between 1995 and 2000.

By contrast, technology industries are estimated to have high beliefs about their steady-state levels of demand between 1995Q1 and 1999Q4, in line with the dot-com exuberance before 2000, and discussed above in footnote 6. The information data industry are estimated to have beliefs about demand of around 4, significantly higher than its true value of 0. This industry includes firms such as IBM and, at present, Google and Facebook.[15] The next highest estimated beliefs about demand are for firms in the durable computing industry, with an estimated demand parameter of 0.7. Firms in this sector include Dell, Hewlett-Packard, and Motorola. We explore the implications of these estimated demand parameters in the next section.

Aggregate Estimates Panel C of Table 2 presents estimates of the persistence and size of the aggregate shock processes. To interpret these, we show the unconditional forecast error variance decompositions of a set of aggregate variables in Table 3. We find that the aggregate shock to the valuation of corporate assets – risk premia shocks – are key drivers of aggregate variables. In reduced-form, this shock has similar implications as the marginal efficiency of investment shocks found to be key drivers of business cycles in Justiniano et al. (2011). Aggregate entry cost shocks are found to explain a significant amount of the variation of investment – about 41% – and the natural rate – about 37%. The Herfindahl, corresponding to the number of firms in the economy in our model, is largely explained by technology shocks (20%), households' preference shocks (20%) and risk premia shocks (49%). Entry cost shocks explain about 8% of the unconditional variance in the number of firms. As shown in counterfactual simulations in the next section, during the period 1989 to 2015, we find an important role for firm entry cost shocks in explaining investment and the natural interest rate.

5 Firm Entry and the Decline in Investment

In this section, we explore the implications of firm entry for investment, aggregate output and monetary policy. We first examine the industry-level implications of our estimates, and show that about 10% of the variation in industry concentration ratios between 1995 and 2000 can be explained by firm entry caused by our estimated beliefs about an industry's long-run demand. The remainder of the variation in relative industry concentration is largely accounted for by transitory entry-cost shocks. We also find that about 10% of the relative variation in the capital stock is accounted for by demand belief shocks, with the remainder of the variation mostly accounted for by risk premia shocks.

We then identify aggregate shocks to firm entry costs and in our main counterfactual, set those entry costs to zero from 2005 onwards. Our findings suggest that entry cost shocks account for much of the increase in concentration, and that once the entry cost shocks are removed, we find substantial effects on aggregate investment, the natural interest rate, and therefore the stance of monetary policy.

[15] See the industry classification codes at `https://siccode.com/en/naicscodes/51/information`.

In the counterfactual exercise, we find that absent the entry cost shocks, the aggregate Herfindahl index would have been about 10% lower by 2014 and the capital stock would have been about 2.5% to 3.5% higher by the start of 2015, depending on how binding the zero lower bound is over 2009 to 2015. In the next section, we show that these entry cost shocks correlate well with empirical proxies of entry barriers, such as regulation, that are not used in the estimation.

5.1 Industry Implications

We first examine the industry-level impulse responses to industry-level shocks for the average industry with an elasticity of substitution between firm-level goods of $\epsilon = 5$, when the remaining model parameters are set to the mode of their estimated posterior distributions. Figure 5a plots the response of goods-producers' Q_t, industry-level concentration, and real output following a one standard deviation transitory demand shock. Following the demand shock, industry-level real output rises, goods-producers' profits increase, and new firms enter, lowering the Herfindahl and the level of concentration in the industry. Our estimate of $\phi_n = 1.5$ implies that entry into the industry is fairly gradual. Given our estimates, the impulse response implies that, following a demand shock that raises goods-producers' Q_t to 10% above steady-state after one year, the number of firms increases by 1.4% after two years. This is consistent with the evidence in Gutiérrez and Philippon (2018).

Figure 5b plots the impulse response of the industry-level observables following a one standard deviation shock to entry costs. Following an increase in entry costs, profits rise and fewer firms enter so that industry concentration increases with the Herfindahl index rising by just over 1%, while industry-level real output falls by about 0.1%. Figure 5c plots the impulse response to a one standard deviation productivity shock, which we find to temporarily lower prices and goods-producers' Q_t, reduce firm entry, and raise real output.

We next explore what the estimated shocks imply for the industry-level variables. In Figure 6 we plot, for the information data industry, the path of the Herfindahl index used in estimation and the path without stochastic shocks but under the estimated demand beliefs only. In Panel B, we also plot the path of the capital stock used in estimation and under demand beliefs only for the information data industry. As discussed earlier, beliefs about steady-state demand are estimated to be strongly positive for the information data industry. Under these optimistic beliefs about long-run demand only, firms enter and the Herfindahl falls by about 5%, which is about half of the observed decline in the relative Herfindahl index between 1995 and 2000. Following the reversion in beliefs back to their true values in 2000, firms exit the industry and the Herfindahl increases. As shown in Panel B, about a quarter of the increase in the relative capital stock observed in the information data industry can also be accounted for using the shock to beliefs about steady-state demand.

Next, we show for all industries how well the expected demand shock captures the change in firm concentration. We compute counterfactual paths for each industry under the expected demand regimes only and plot, in Figure 7, the change in the observed Herfindahl from 1995 to 2000 against the change in Herfindahl predicted by our model and the estimated demand regime beliefs alone. Across all industries, the slope of the regression line between the observed and predicted change is 0.06, while the correlation is about 0.4. In Panel B, we plot the change in the industry capital stock in the data from 1995 to 2000 against the capital stock predicted by our model and the expected demand beliefs only in 1995. The slope of the fitted line between capital observed and that predicted by expected demand beliefs is 0.14, while the correlation is 0.76. There is also a slightly positive relationship between the level of Q_t predicted by expected demand beliefs in 1995 and the change in observed Q_t, with a correlation between the predicted and actual levels of 0.14.

5.2 Aggregate Implications

In this section, we explore our estimated model's implications for aggregate variables. We first obtain the smoothed shocks that generate the aggregate data.[16] With those shocks, we generate a counterfactual series by setting the entry cost shocks to zero from 2003Q1 on, assuming that the zero lower bound can bind under those shocks, and that the Federal Reserve does not implement forward guidance when faced with a binding zero lower bound. The simulation results are plotted in Figure 8. Under this counterfactual, there is substantially more firm entry. Panel A plots the Herfindahl index in the data and in our counterfactual. By 2006Q1, the Herfindahl is 4.1% lower without entry cost shocks, 11.2% lower by 2008Q1, and 6.7% lower by 2014Q1. We find that this counterfactual entry has substantial aggregate effects, even when monetary policy does not react to shocks that caused the Great Recession. In Panel B we show that, while the Fed Funds rate would have been at its zero lower bound for much of the 2009Q1 to 2015Q1 period, it would have been positive between 2010 and 2012.

In addition, Figure 8 plots how the economy would have reacted under all shocks but where monetary policy is not constrained by the zero lower bound. In this case, we estimate that the zero

[16] For this experiment, we keep the Herfindahl fixed at its 2012Q1 level from 2012Q1 on. This ensures our Herfindahl series is consistent with the patterns observed in Census data (available only until 2012), and mitigates the issues with relative prices and weights during the financial crisis, as documented in Figure A.1 in the Appendix.

lower bound would have been a significantly constraint on monetary policy from 2012 so that, by 2015Q1, we estimate that the Fed would have lowered the Fed Funds rate by almost 2 percentage points (Panel B). This observation that the zero lower bound was not a significantly binding constraint early on in the zero lower bound episode is consistent with estimates of the shadow interest rate bottoming out by 2014/15 (see Wu and Xia, 2016). In Panel A, we see that if the Fed had been able to lower the Fed Funds rate below zero, the monetary stimulus would have encouraged firm entry: the Herfindahl index in this case would have fallen by almost 2 percentage points by 2012Q1, and by 6 percentage points by 2015Q1. This counterfactual illustrates the importance of modeling entry alongside the zero lower bound, as firm entry depends critically on the state of the economy, and not by entry cost shocks alone.

Next, we explore what our model predicts for investment and consumption. Figure 9 plots the level of capital, in Panel A, and the level of consumption, in Panel B, both in the data and in two simulations: (i) without the zero lower bound and all shocks, and (ii) without the zero lower bound but with entry cost shocks set to zero from 2003 onwards. The additional monetary stimulus during the zero lower bound period would have caused both capital and consumption to be higher between 2009 and 2015. In particular, the capital stock would have been higher by about 1.4% by 2015, and consumption would have been higher by about 5.5% by 2015. On top of this, we find a key role for entry cost shocks. If we were to simulate the economy absent entry cost shocks from 2003 and absent the zero lower bound, we find that the level of the capital stock would be higher (relative to that observed) by 3.5% by 2015, and the level of consumption by 11% by 2015. We conclude therefore that entry cost shocks have had a significant effect on aggregate quantities and that modeling monetary policy during the zero lower bound is crucial to determine the aggregate effects of entry cost shocks.

As highlighted, the aggregate effect of the identified decline in firm entry can be separated into the direct channel caused by a fewer number of firms investing, and an indirect channel caused by the binding zero lower bound and the inability of monetary policy to accommodate further declines in the natural rate. To illustrate the interaction between entry cost shocks and a binding zero lower bound, we plot the natural interest rate implied by the data and the Kalman filter, against the natural interest rate computed in a simulation where entry cost shocks are removed. Figure 10 plots the natural rate implied by the data and in two simulations: when entry cost shocks are removed from 2000 to 2015, and when entry cost shocks are removed during the ZLB period only. The simulations show the important role that firm entry has had in explaining movements in the natural rate. Comparing both simulations against the data-implied natural rate, our estimates imply that the positive entry cost shocks caused the annualized natural rate to fall by an additional 2.8 percentage points by 2011Q1, while keeping it depressed through to 2015.

6 Explaining the Rise in Entry Costs

Our model suggests that rising entry costs had a substantial effect on aggregate trends. We conclude by showing that the estimated entry cost shocks are correlated with empirical proxies of barriers to entry at the industry-level – namely regulation and M&A activity.[17] The link between regulation and entry costs is the subject of a long literature. Davis (2017) discusses recent evolutions for the U.S. and Gutiérrez and Philippon (2018) study the relationship empirically. The link between M&A and entry costs is more tenuous. Easing of M&A restrictions – as documented by Kwoka (2015) – allow incumbents to consolidate and potentially increase barriers to entry. But M&A may increase for other reasons, including demand shocks and technological change (Andrade et al., 2001).

Figure 11 shows that aggregate entry cost shocks closely relate to regulation and M&A activity. It plots the aggregate entry-cost shock ζ_t^{κ} against log-changes in regulation (left) and M&A activity (right). Measures of M&A activity are based on Thomson Reuters SDC. Measures of regulation are based on RegData 3.1, introduced in Al-Ubaydli and McLaughlin (2015).[18] RegData is a substantial improvement relative to simple page counts but, given the sheer scale of regulation, measuring regulatory stringency at the industry level is a challenging task. To control for measurement error, we complement RegData with measures of regulatory employment from the Census' Occupational Employment Statistics in some of our tests.[19]

Figure 12 shows that entry cost shocks are closely related to Regulation and M&A activity for two

[17] One might worry that the estimated entry costs are driven by technological change or are unrelated to barriers to entry. To test this, Figure A.4 plots the average entry cost shock by industry, against the industry's intangible intensity. As shown, there does not appear to be a positive relationship between the two. We find similar results using alternate measures of intangible intensity (e.g., changes, initial levels, etc.)

[18] RegData relies on machine learning and natural language processing techniques to construct measures of regulatory stringency at the industry level. In particular, it counts the number of restrictive words or phrases such as 'shall', 'must' and 'may not' in each section of the Code of Federal Regulations and assigns them to industries. Goldschlag and Tabarrok (2018) provide several validation analyses for RegData such as comparing to the size of relevant regulatory agencies and the employment share of lawyers in each industry. They conclude that "the relative values of the regulatory stringency index capture well the differences in regulation over time, across industries, and across agencies." We use log-changes in regulation throughout our analyses. Gutiérrez and Philippon (2018) emphasize using absolute changes when considering a long history because regulation increased rapidly from a low initial level in the 1970s, which exaggerates log-changes early in the sample. Our sample period is more recent and log-changes appear well-behaved.

[19] In particular, we consider changes in the number of employees in Legal and Compliance occupations (SOC codes 23-0000 and 13-1040, respectively), by industry. Data following the NAICS hierarchy is available only after 2002, which limits our sample – but we still find a robust relationship.

important industries, which exhibit some of the highest average entry cost shocks – Durable Computer Manufacturing and Transportation Air. The patterns for Transportation Air closely align with a recent (and controversial) merger wave that included Delta-Northwest (2008), United-Continental (2010), Southwest-AirTran (2011) and American-US Airways (2014).

Table 4 confirms these relationships across all industries. We regress $\zeta^{\kappa}_{j,t}$ on measures of regulation and M&A at the industry-level. All regressions include year fixed effects given that $\zeta^{\kappa}_{j,t}$ are estimated relative to aggregate shocks, and industry fixed effects to control for unobserved variation. Column 1 includes the full sample, since 1989, and uses the regulation indices from RegData. Columns 2 and 3 consider our alternate measures of regulation over the industry-years when both are available (after 2002). As shown, both measures are positively correlated with entry cost shocks. To control for measurement error, column 4 takes the average between both measures. As expected, the t-statistic in column 4 increases substantially.[20] Columns 5 and 6 replicate column 1 and 4, adding a measure of M&A activity.

7 Conclusions

Entry has decreased in the US economy, and markets have become more concentrated. We find that entry costs shocks have played an important role and that they are related to entry regulations. The methodology we use in this paper, mixing a structural model with cross-sectional evidence, can usefully be applied to other contexts.

[20] In unreported tests, we instrument changes in the regulation index with changes in regulatory employment. We find consistent albeit somewhat noisy results given the short time-period.

References

Al-Ubaydli, Omar and Patrick A. McLaughlin, "RegData: A numerical database on industry-specific regulations for all United States industries and federal regulations, 1997 to 2012," *Regulation & Governance*, 2015. 6, A.1.2

Alexander, Lewis and Janice Eberly, "Investment Hollowing Out," *Working Paper*, 2016. 1

Anderson, Keith, Chris Brooks, and Apostolos Katsaris, "Speculative bubbles in the S&P 500: Was the tech bubble confined to the tech sector?," *Journal of Empirical Finance*, jun 2010, *17* (3), 345–361. 6

Andrade, Gregor, Mark Mitchell, and Erik Stafford, "New Evidence and Perspectives on Mergers," *Journal of Economic Perspectives*, may 2001, *15* (2), 103–120. 6

Autor, David, David Dorn, Lawrence Katz, Christina Patterson, and John Van Reenen, "Concentrating on the Fall of the Labor Share," Technical Report, mimeo jan 2017. 1, 1

Barkai, Simcha, "Declining Labor and Capital Shares," 2017. University of Chicago. 1

Bilbiie, Florin, Fabio Ghironi, and Marc Melitz, "Endogenous Entry, Product Variety, and Business Cycles," 2012. 1

Blonigen, Bruce A. and Justin R. Pierce, "Evidence for the Effects of Mergers on Market Power and Efficiency," Working Paper 22750, National Bureau of Economic Research October 2016. 1

CEA, "Benefits of Competition and Indicators of Market Power," Issue Brief April 2016. 1, 1

Crouzet, Nicolas and Janice Eberly, "Intangibles, Investment, and Efficiency," *AEA Papers and Proceedings*, 2018. 1

Davis, Steven, "Regulatory Complexity and Policy Uncertainty: Headwinds of Our Own Making," 2017. Booth Working Paper. 6

De Loecker, Jan and Jan Eeckhout, "The Rise of Market Power and the Macroeconomic Implications," 2017. 1

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, "Where Has All the Skewness Gone? The Decline in High-Growth (Young) Firms in the U.S," Working Papers 15-43, Center for Economic Studies, U.S. Census Bureau November 2015. 1

Doms, Mark C., "The boom and bust in information technology investment," *Economic Review*, 2004, pp. 19–34. 6

Dottling, Robin, Germán Gutiérrez, and Thomas Philippon, "Is there an investment gap in advanced economies? If so, why?," 2017. mimeo. 1

Eggertsson, Gauti and Michael Woodford, "The Zero Bound on Interest Rates and Optimal Monetary Policy," *Brookings Papers on Economic Activity*, 2003, *1*, 139–234. 1

Eggertsson, Gauti B., Jacob A. Robbins, and Ella Getz Wold, "Kaldor and Piketty's Facts: The Rise of Monopoly Power in the United States," Working Paper 24287, National Bureau of Economic Research February 2018. 1

_ , Neil R. Mehrotra, and Jacob A. Robbins, "A Model of Secular Stagnation: Theory and Quantitative Evaluation," *American Economic Journal: Macroeconomics*, 2019. 1

Feenstra, Robert C. and David E. Weinstein, "Globalization, Markups and U.S. Welfare," *Journal of Political Economy*, 2017. 2

Fernández-Villaverde, Jesús, Grey Gordon, Pablo Guerrón-Quintana, and Juan F. Rubio-Ramírez, "Nonlinear adventures at the zero lower bound," *Journal of Economic Dynamics and Control*, 2015, *57*, 182–204. 1

Furman, Jason, "Business Investment in the United States: Facts, Explanations, Puzzles, and Policies," Technical Report, CEA 2015. 1, 1, 3

Gali, Jordi, *Monetary Policy, Inflation, and the Business Cycle*, Princeton University Press, 2008. 3.3

Goldschlag, Nathan and Alex Tabarrok, "Regulatory Burden," *Economic Policy*, 2018. 18, 22

Gompers, Paul and Josh Lerner, "The Venture Capital Revolution," *Journal of Economic Perspectives*, may 2001, *15* (2), 145–168. 6

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, "Are US Industries Becoming More Concentrated?," Technical Report, Working paper 2016. 1, 1, 2

Guerrieri, Luca and Matteo Iacoviello, "OccBin: A Toolkit for Solving Dynamic Models With Occasionally Binding Constraints Easily," *Journal of Monetary Economics*, 2015, pp. 23–38. 4.4

Gutiérrez, Germán and Thomas Philippon, "Investment-less Growth: An Empirical Investigation," *Brookings Papers on Economic Activity*, 2017, *Fall.* 1, 2, 4.3, 13

_ and _ , "The Failure of Free Entry," 2018. 5.1, 6, 18

Hogendorn, Christiaan, "Excessive(?) entry of national telecom networks, 1990–2001," *Telecommunications Policy*, dec 2011, *35* (11), 920–932. 6

Jones, Callum, "Unanticipated Shocks and Forward Guidance at the Zero Lower Bound," 2017. mimeo NYU. 4.4

_ , "Aging, Secular Stagnation and the Business Cycle," 2018. Working Paper NYU. 1

_ , Virgiliu Midrigan, and Thomas Philippon, "Household Leverage and the Recession," mimeo 2018. 4.4, 4.5

Justiniano, Alejandro and Giorgio Primiceri, "The Time-Varying Volatility of Macroeconomic Fluctuations," *The American Economic Review*, 2008, *98* (3), 604–641. 4.1

_ , _ , and Andrea Tambalotti, "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 2011, *14* (1), 101–121. 3.5, 4.6

Kulish, Mariano and Christopher Gibbs, "Disinflations in a Model of Imperfectly Anchored Expectations," *European Economic Review*, 2017, *100* (C), 157–174. 4.4

_ , James Morley, and Timothy Robinson, "Estimating DSGE Models with Zero Interest Rate Policy," *Journal of Monetary Economics*, 2017, *88*, 35–49. 4.3

Kwoka, John, *Mergers, Merger Control, and Remedies*, MIT Press, 2015. 6

Lee, Dong Wook, Hyun-Han Shin, and Rene M. Stulz, "Why Does Capital No Longer Flow More to the Industries with the Best Growth Opportunities?," *Fisher College of Business Working Paper*, September 2016, *2016* (15). 1

Lucas, Robert E. and Edward C. Prescott, "Investment under Uncertainty," *Econometrica*, 1971, *39*, 659–682. 3.1

NVCA, "The Economic Importance of Venture Capital Backed Companies to the U.S. Economy," Technical Report, National Venture Capital Association, Thomson Reuters 2010. 6

Peters, Ryan H. and Lucian A. Taylor, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 2016. A.1.3, A.2

Pierce, Justin R. and Peter K. Schott, "A concordance between ten-digit U.S. Harmonized System codes and SIC/NAICS product classes and industries," 2012. 4.3, A.1.3

Smets, Frank and Rafael Wouters, "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, June 2007, *97* (3), 586–606. A.1.1

Summers, Lawrence H., "Why Stagnation Might Prove to be the New Normal," 2013. Financial Times. 1

Swanson, Eric and John Williams, "Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates," *American Economic Review*, 2014, *104*, 3154–3185. 1

Wu, Jing Cynthia and Fan Dora Xia, "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit, and Banking*, 2016, *48* (2-3), 253–291. 5.2

Table 1: Assigned Parameters

Parameter	Value	Description	Source/Target
ν	2	Inverse labor supply elasticity	
β	0.99	Discount factor	
θ_p	2/3	Price setting Calvo probability	Average price contract of 3Q
θ_p	3/4	Wage setting Calvo probability	Average wage contract of 4Q
ϕ_k	20	Capital adjustment cost	Industry regression of $x_{j,t}$ and $Q_{j,t}$
α	1/3	Capital share	
δ	0.1/4	Capital depreciation rate	
δ_n	0.09/4	Exogenous firm exit rate	Average annual % firm exit
ϕ_r	0.86	Interest rate smoothing	Justiniano and Primiceri (2008)
ϕ_p	1.71	Weight on inflation deviations	Justiniano and Primiceri (2008)
ϕ_y	0.05	Weight on output gap	Justiniano and Primiceri (2008)
ϵ_j	2.5 to 14.3	Industry substitution elasticity	$\text{GOS}_j/\text{Nominal Output}_j$ in 1993

Table 2: Estimated Parameters

	Prior				Posterior			
Parameter	Dist	Median	10%	90%	Mode	Median	10%	90%
A. Structural Parameters								
σ	N	2.0	0.8	3.3	0.400	0.402	0.378	0.425
ϕ_n	N	3.0	2.4	3.6	1.309	1.549	1.078	2.319
B. Industry Shock Processes								
$\tilde{\rho}_q$	B	0.5	0.2	0.8	0.002	0.003	0.001	0.006
$\tilde{\rho}_\kappa$	B	0.5	0.2	0.8	0.083	0.100	0.042	0.178
$\tilde{\rho}_d$	B	0.5	0.2	0.8	0.997	0.997	0.995	0.998
$\tilde{\rho}_a$	B	0.5	0.2	0.8	0.918	0.919	0.907	0.930
$\tilde{\rho}_e$	B	0.5	0.2	0.8	0.038	0.061	0.024	0.119
$10 \times \tilde{\sigma}_q$	IG	0.6	0.3	1.9	3.088	3.100	3.039	3.161
$\tilde{\sigma}_\kappa$	IG	0.6	0.3	1.9	0.295	0.311	0.262	0.361
$10 \times \tilde{\sigma}_d$	IG	0.6	0.3	1.9	0.047	0.049	0.040	0.059
$\tilde{\sigma}_a$	IG	0.6	0.3	1.9	0.094	0.095	0.085	0.106
$10 \times \tilde{\sigma}_e$	IG	0.6	0.3	1.9	0.415	0.413	0.388	0.435
C. Aggregate Shock Processes								
ρ_z	B	0.5	0.2	0.8	0.986	0.986	0.984	0.989
ρ_b	B	0.5	0.2	0.8	0.920	0.919	0.905	0.930
ρ_e	B	0.5	0.2	0.8	0.914	0.912	0.901	0.922
ρ_q	B	0.5	0.2	0.8	0.969	0.970	0.966	0.977
ρ_κ	B	0.5	0.2	0.8	0.792	0.786	0.761	0.808
$100 \times \sigma_z$	IG	0.6	0.3	1.9	0.862	0.854	0.784	0.937
$100 \times \sigma_b$	IG	0.6	0.3	1.9	0.284	0.288	0.257	0.326
$100 \times \sigma_e$	IG	0.6	0.3	1.9	0.084	0.086	0.078	0.095
$100 \times \sigma_q$	IG	0.6	0.3	1.9	0.105	0.103	0.091	0.116
$100 \times \sigma_i$	IG	0.6	0.3	1.9	0.128	0.132	0.120	0.147
$100 \times \sigma_\kappa$	IG	0.6	0.3	1.9	0.379	0.384	0.350	0.421

Table 3: Variance Decomposition of Aggregate Variables

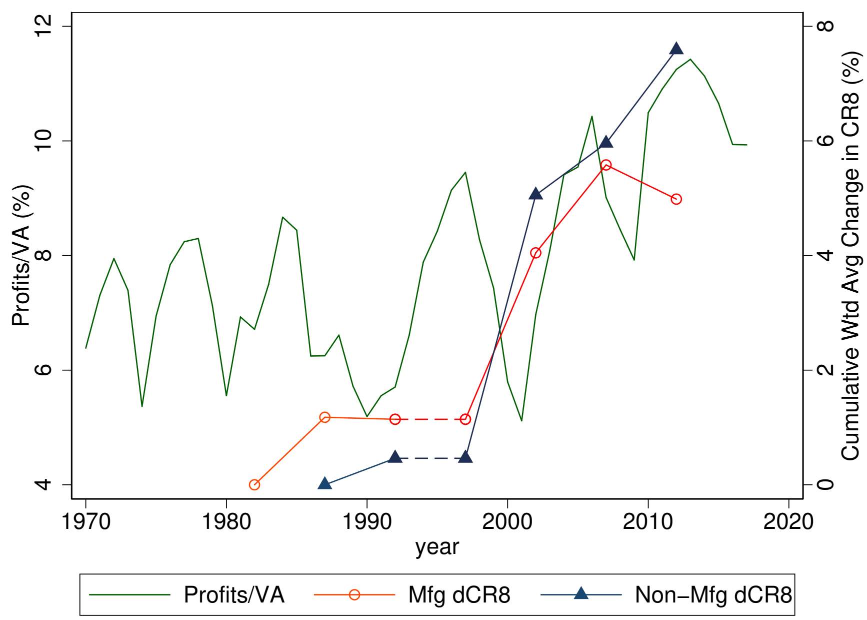
Variable \ Shock	Technology	Preference	Markup	Risk Premia	Policy	Entry Cost
Fed Funds Rate	26.9	2.3	14.5	41.8	8.9	5.7
Output	15.7	21.4	1.1	51.0	1.1	9.7
Consumption	28.1	18.2	1.2	44.7	0.9	7.0
Investment	8.9	17.3	1.7	28.5	2.5	41.2
Employment	23.2	19.3	1.4	47.1	1.1	8.0
Inflation	30.6	0.3	24.1	32.7	7.1	5.2
Herfindahl	20.5	20.2	1.0	49.0	1.0	8.3
Natural Rate	1.3	6.7	0.0	54.9	0.0	37.1

Table 4: Regression of Entry Cost Shocks vs. Regulation and M&A

This table reports regression results of industry-level entry cost shocks on measures of regulation and M&A activity. Measures of regulation are standardized to ensure comparability. Entry cost shocks estimated using the model. Regulation indices from RegData. Changes in regulatory employment based on the Census' OES. M&A activity from Thomson Reuters SDC. Standard errors clustered at the industry-level in brackets. + p<0.10, * p<0.05, ** p<.01.

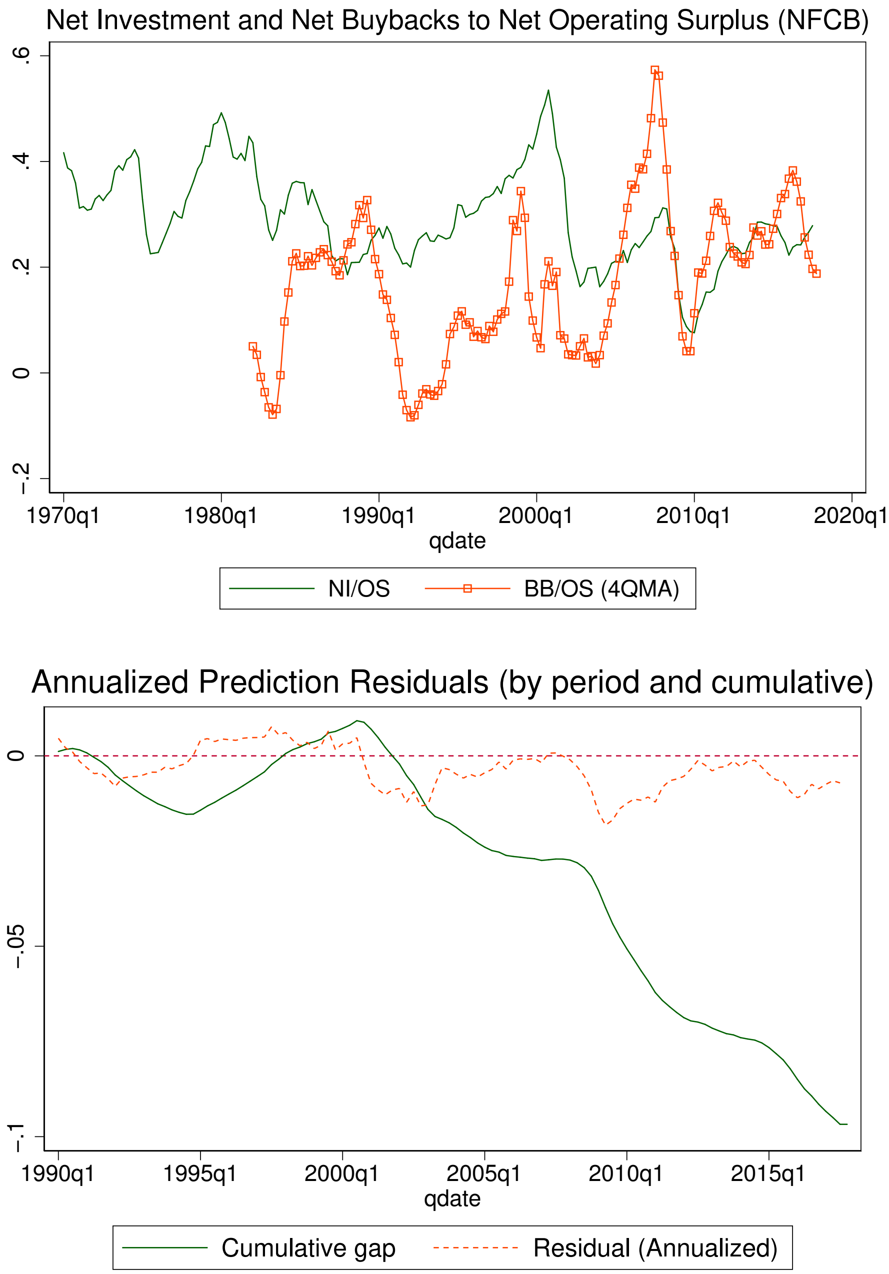
	$\zeta^{\kappa}_{j,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Post-02	Post-02	Post-02	All	Post-02
$\Delta\log(Reg\,Index^{j}_{t-2,t-1})$	0.045^{**}	0.051^{**}			0.045^{**}	
	(0.014)	(0.018)			(0.014)	
$\Delta\log(Reg\,Emp^{j}_{t,t+1})$			0.037^{**}			
			(0.013)			
Mean(L.dRegIndex,F.dRegEmp)				0.043^{**}		0.037^{**}
				(0.010)		(0.011)
$\log(M\&A_{j,t})(2YMA)$					0.050^{*}	0.104^{*}
					(0.022)	(0.042)
Ind FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
R2	.051	.097	.091	.1	.058	.12
Observations	837	358	358	358	837	358

Figure 1: Concentration and Profits



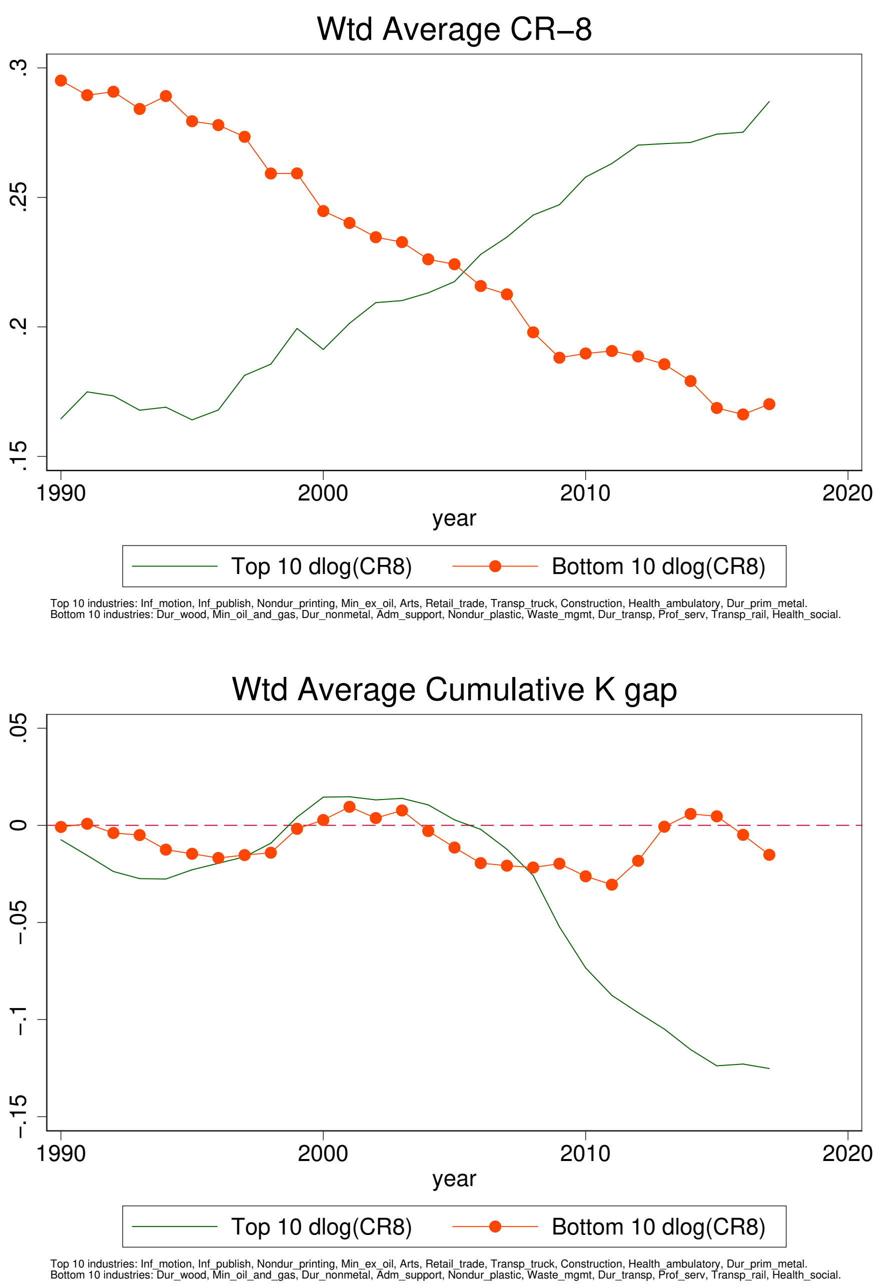
Notes: Solid line plots ratio of After Tax Corporate Profits with IVA and CCAdj to Value Added for the U.S. Non-Financial Corporate sector (series W328RC1A027NBEA and NCBGVAA027S, respectively). Annual data from the Financial Accounts of the United States, via FRED. Dotted lines show the cumulated sales-weighted average change in 8-firm Concentration Ratio (CR8). Data from the U.S. Economic Census based on SIC codes before 1992 and NAICS codes after 1997. We include only those industries that are consistently defined over each 5-year period, so that no change is measured from 1992 to 1997. When multiple tax groups are reported, only taxable firms are included. CR8 equals the market share (by sales) of the 8 largest firms in each industry.

Figure 2: Net Investment, Profits and Q-Residuals



Notes: Quarterly data from the Financial Accounts of the United States, via FRED. Top plot shows the ratio of net investment and net buybacks to net operating surplus for U.S. Non Financial Corporate sector. Bottom plot shows the per-period and cumulative residuals of a regression of net investment for the U.S. Non Financial Business sector on Q for Non Financial Corporate sector. We use the 1990 to 2001 period as a training sample and use the estimated coefficients to forecast out-of-sample after 2001. See Appendix A for additional details.

Figure 3: Cumulative Capital Gap for Concentrating and Non-Concentrating Industries



Notes: Annual data. Top plot shows the weighted average import adjusted 8-firm Concentration Ratio (CR8) for the 10 industries with the largest and smallest log-change in import-adjusted CR8 between 2000 and 2017. Bottom plot shows the cumulative implied capital gap (as a percent of capital stock) for the corresponding industries. See text for details.

Figure 4: Mode of Estimated Posterior Distributions of Expected Demand Across Industries

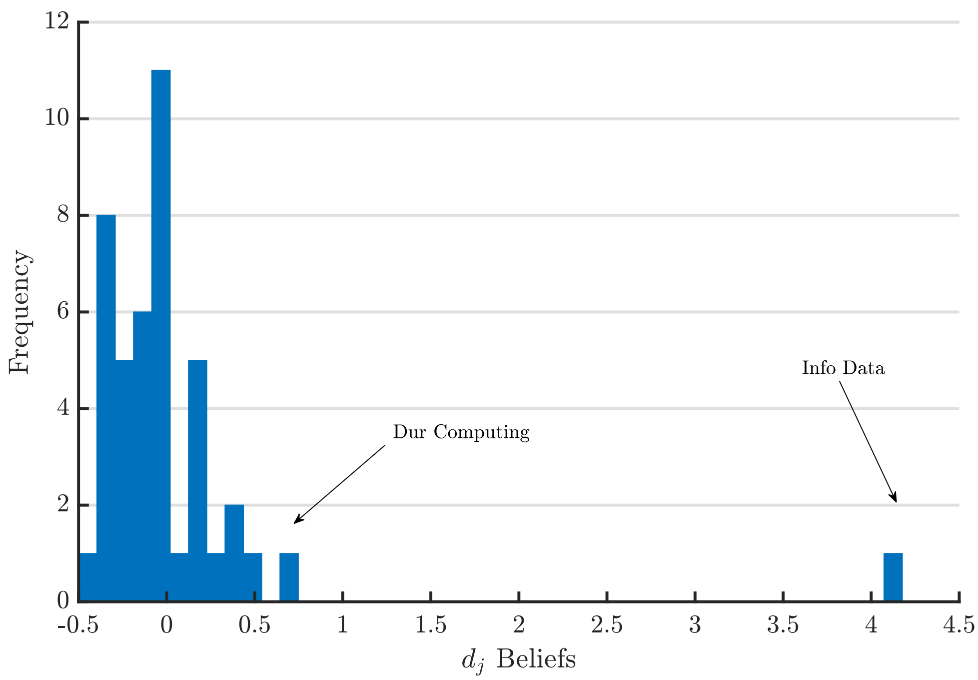
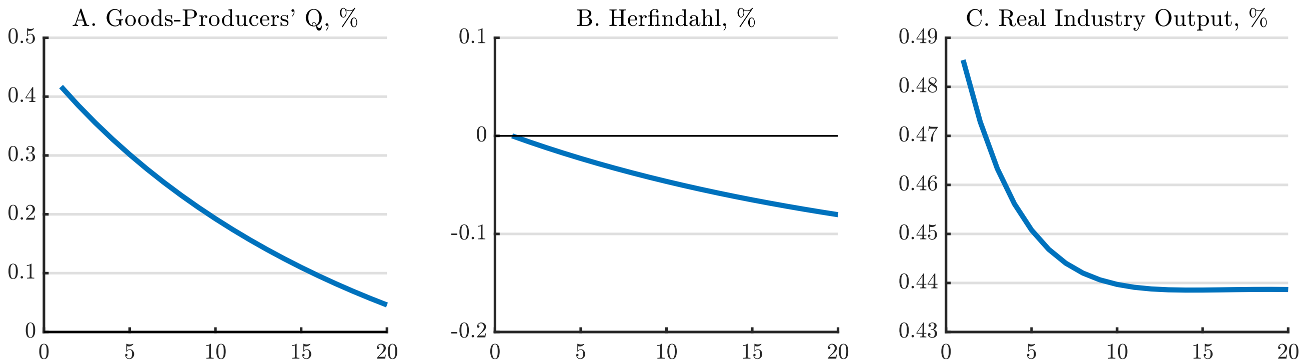
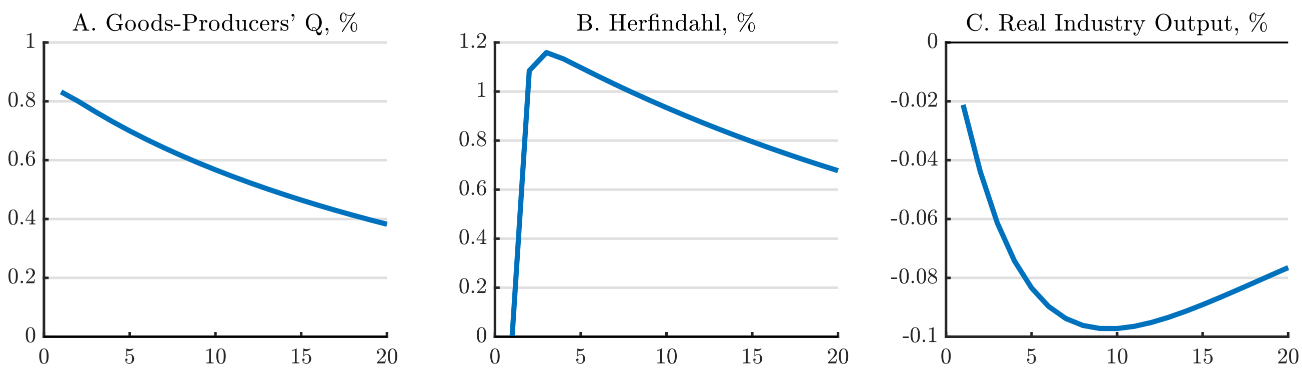


Figure 5: Industry-Level Impulse Response Functions

(a) Industry-Level Impulse Responses to Demand Shock



(b) Industry-Level Impulse Responses to Entry-Cost Shock



(c) Industry-Level Impulse Responses to Productivity Shock

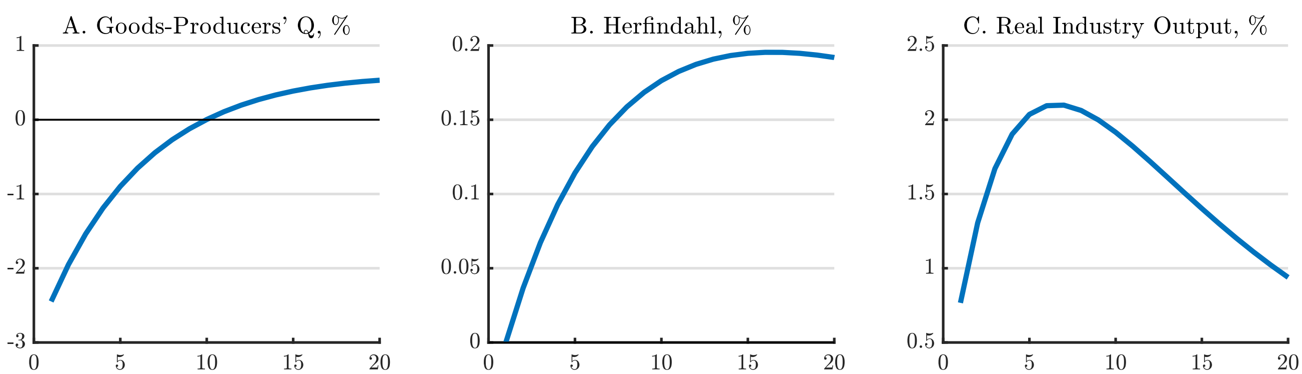


Figure 6: Information Data Industry, Identified Demand Belief Shock

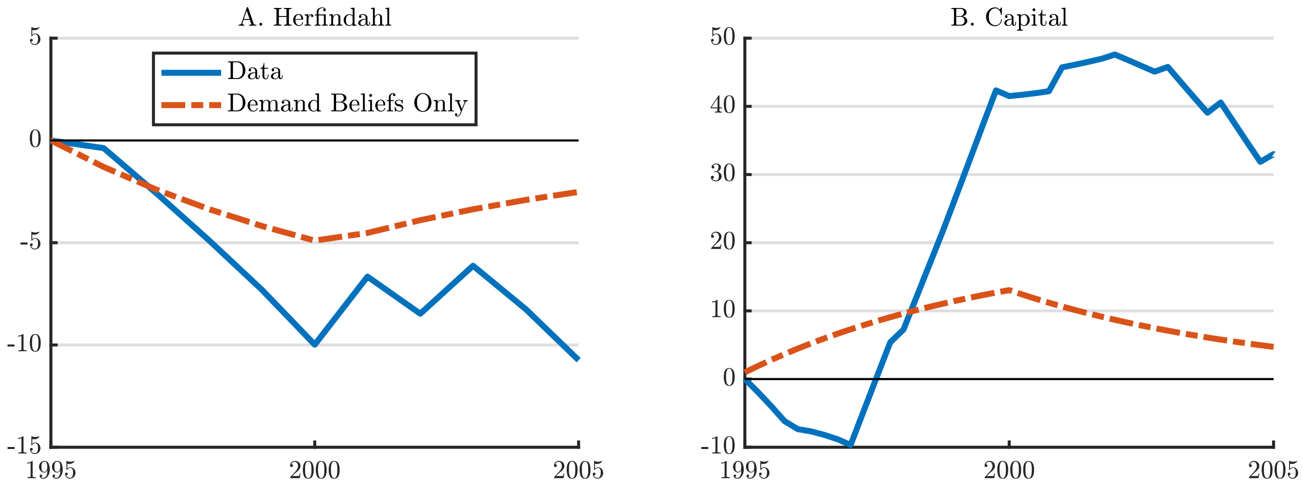


Figure 7: Industry Counterfactual, Demand Belief Shocks Only

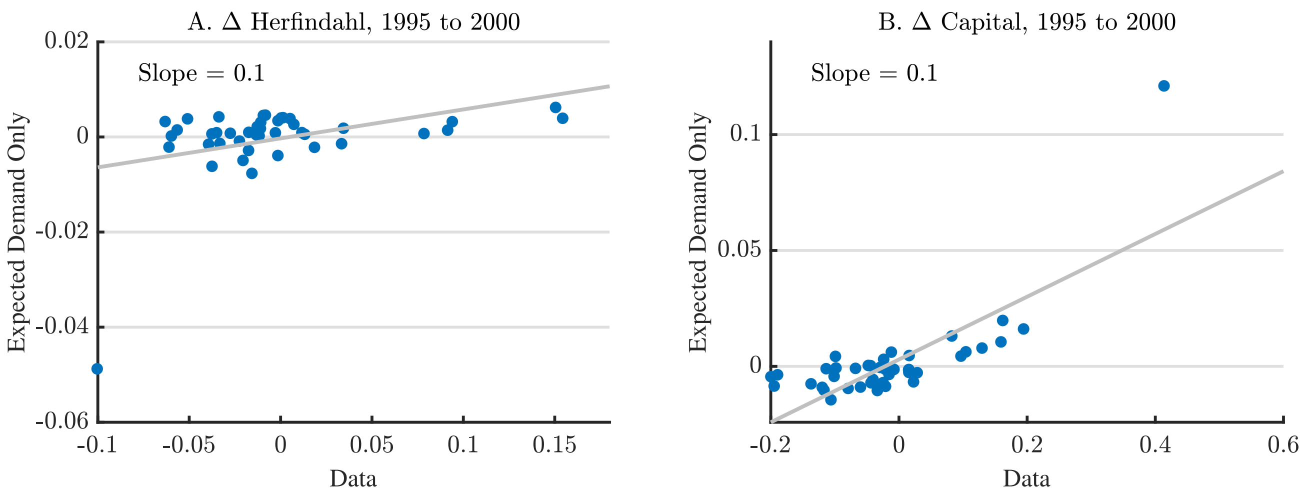


Figure 8: Aggregate Counterfactual, Entry and Monetary Policy

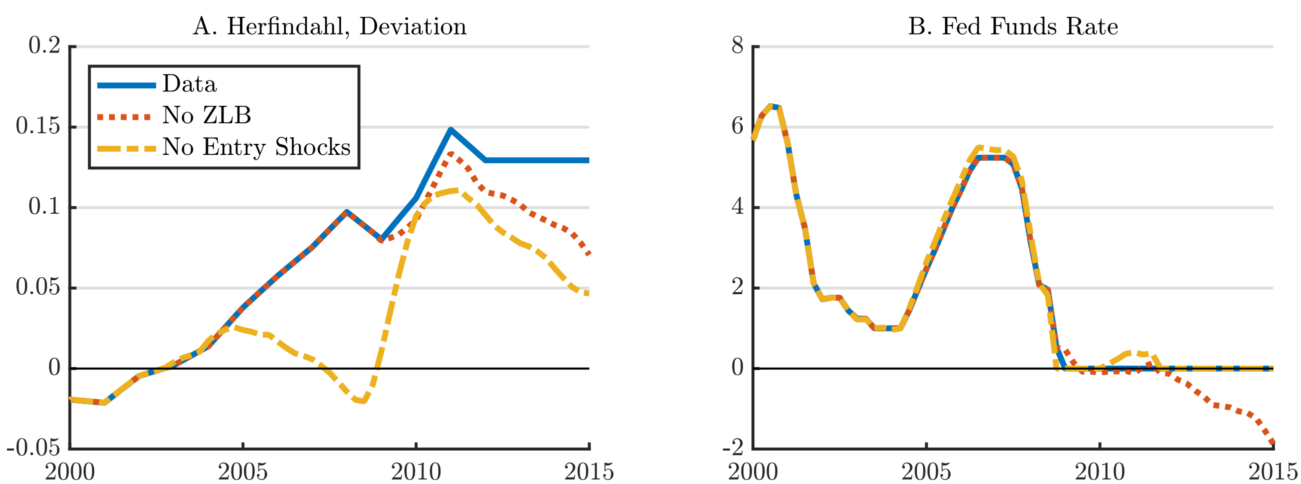


Figure 9: Log Capital and Consumption, Without ZLB and Without Entry Cost Shocks

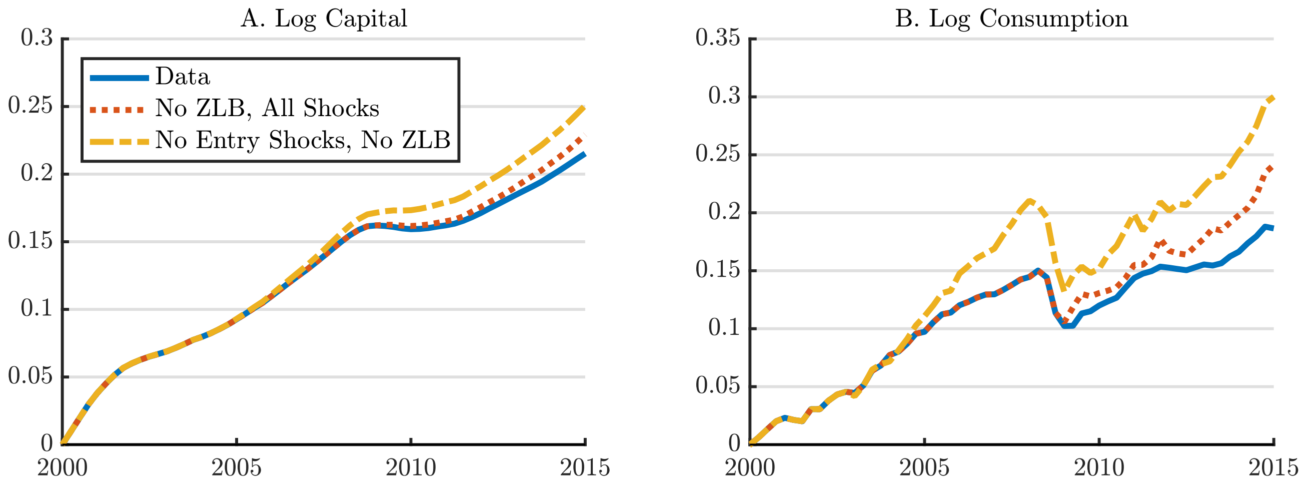


Figure 10: Natural Interest Rate, No Entry Shocks, Annual

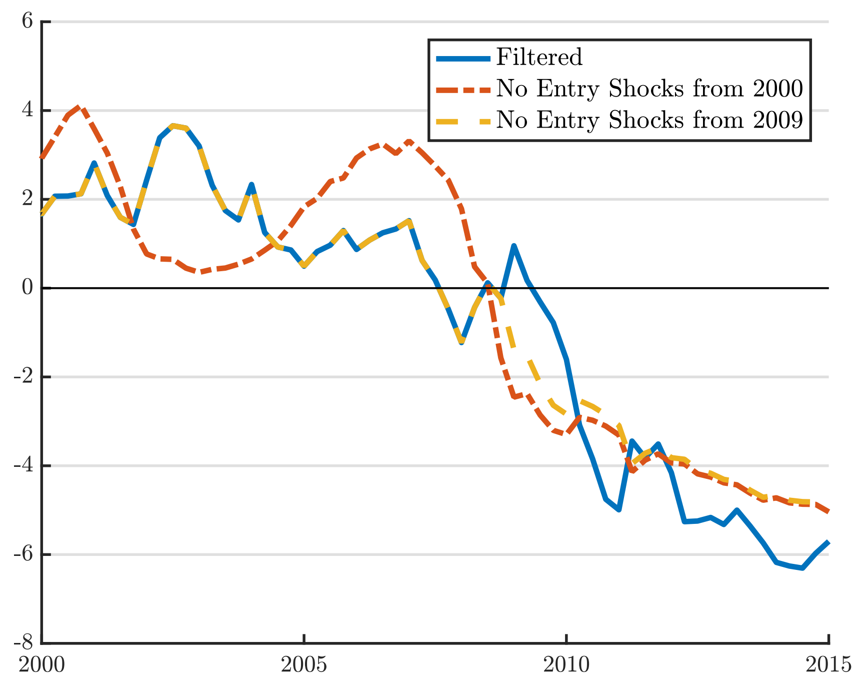
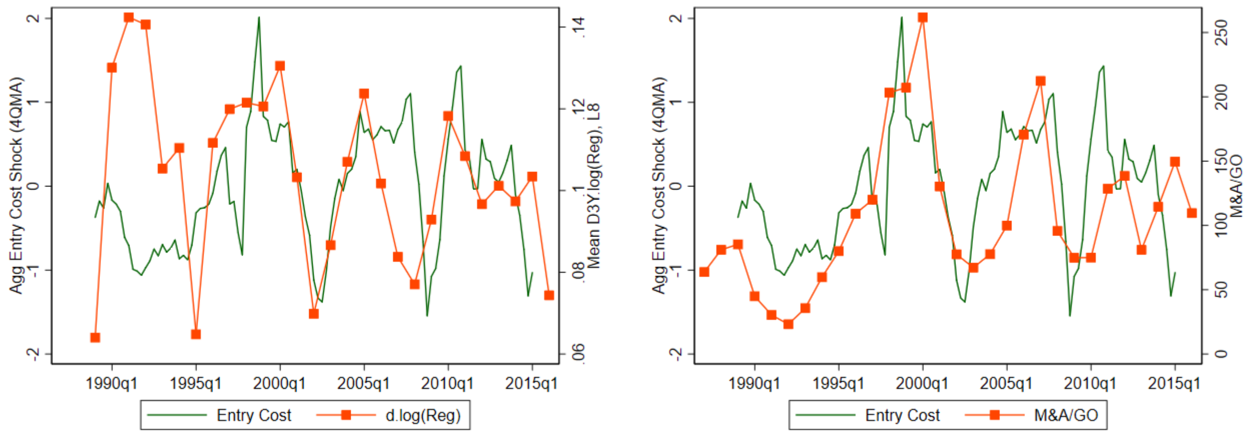
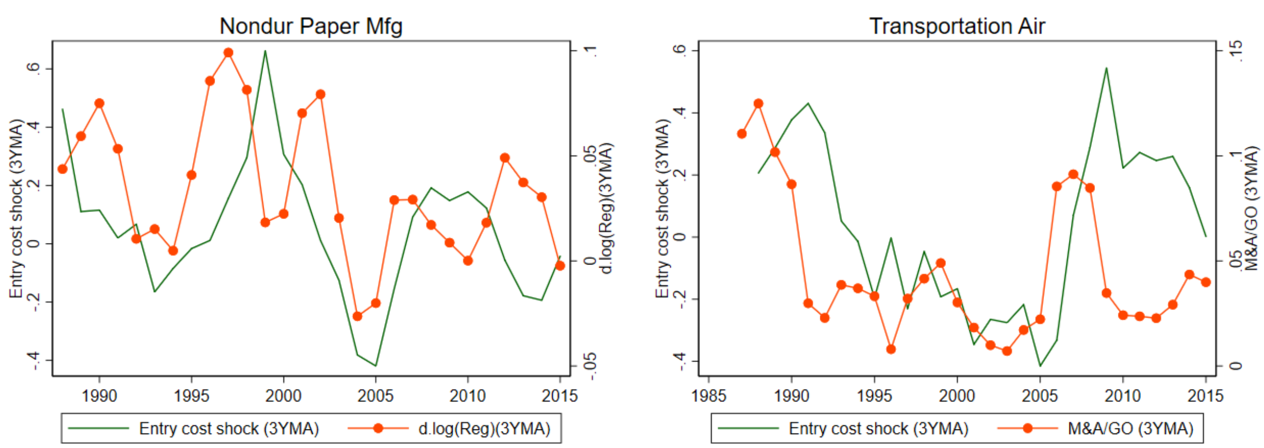


Figure 11: Aggregate Entry Cost Shocks vs. Regulation and M&A



Notes: Annual data. Entry cost shocks estimated by the model. Regulation indices from RegData. M&A activity from Thomson Reuters SDC.

Figure 12: Industry Entry Cost Shocks vs. Regulation and M&A



Notes: Annual data. Entry cost shocks estimated by the model. Regulation indices from RegData. M&A activity from Thomson Reuters SDC.

Appendix

A Data Sources and Definitions

We use a wide range of aggregate-, industry- and firm-level data, summarized in Table A.1 and described in the rest of this section.

Table A.1: Summary of Key Data Sources

	Source	Key Data fields	Granularity
Aggregate	Federal Reserve Economic Database	$\bar{r}_t$, π_t^p, c_t, x_t, ℓ_t	Aggregate
	Financial Accounts of the United States	I, K, OS, and Q	Sector (NFCB, NFNCB)
Industry	BEA GDP by Industry	Output & prices	˜NAICS L3
	BEA Fixed Assets Tables	I, K	˜NAICS L3
	Economic Census	Concentration	NAICS L3-L6
	Peter Schott's website	Imports	NAICS L6
	Census OES	Employment by occupation	NAICS L3-L6
	RegData	Regulation Index	NAICS L3-L6
Firm	Compustat NA	Q, I, K and OS	Firm
	Peters & Taylor	Intangible K	Firm
	Thomson Reuters SDC	M&A deal value	Transaction

A.1 Data Sources and Definitions

A.1.1 Aggregate Data

FRED. For use in the model, we gather the change in real consumption per capita, the net investment rate, inflation, and employment from FRED. We follow Smets and Wouters (2007) in using the GDP deflator for inflation (FRED code GDPDEF), constructing real consumption per capita (FRED code PCEC divided by the GDPDEF, and the index of civilian non-institutional population CNP16OV),[21] and non-farm business hours (FRED code PRS85006023 times the civilian employment level CE16OV, divided by the index CNP16OV). Our aggregate measure of the concentration ratio is the weighted average by sales of the top-4 firm, import-adjusted, concentration ratio obtained from Compustat. Consumption, inflation, and the concentration ratio are demeaned prior to estimation.

Financial Accounts of the U.S. For our motivating analyses, we gather quarterly data for the Non-Financial Corporate and Non-Financial Non-Corporate sectors of U.S. Data is sourced from the

[21] We also smooth CNP16OV to account for jumps in the series.

Financial Accounts of the United States via FRED. See Section A.2 below for details on the data series and definitions used for each Figure.

A.1.2 Industry-level data

Investment and Capital Stocks. Industry-level investment and capital stocks are gathered from the Section 3 of the BEA Fixed Assets tables, available at link. Data includes current-cost and chained values for the net stock of capital, depreciation and investment. Note that BEA I and K include intangible assets (i.e., software, R&D, and some intellectual property), not just tangible capital.

The data includes 63 granular industry groupings. We group these industries into 47 categories to ensure all groupings have material investment; reasonable Compustat coverage; and yield stable investment and concentration time series. In particular, we group industries so that each group contains at least ∼10 firms, on average, and contributes a material share of output and investment. We exclude Financials and Real Estate; and also exclude Utilities given the influence of government actions in their investment. Last, we exclude 'Management of companies and enterprises' because there are no companies in Compustat that map to this category. This leaves 43 industry groupings, summarized in Table A.2. All other datasets are mapped into these 43 industry groupings.

Output and Prices. Nominal Gross Output and Prices are gathered from the BEA's GDP by Industry accounts (file GDPbyInd_GO_1947-2017). Industry segments closely follow those of the Fixed Assets tables.

Regulation Index. We gather industry-level regulation indices from RegData 3.1, available at link and introduced in Al-Ubaydli and McLaughlin (2015). RegData aims to measure regulatory stringency at the industry-level. It relies on machine learning and natural language processing techniques to count the number of restrictive words or phrases such as 'shall', 'must' and 'may not' in each section of the Code of Federal Regulations and assign them to industries.[22] Note that most, but not all industries are covered by the index. We map the Regulation index to BEA segments by selecting the closest NAICS industry(s) to a given BEA segments.[23] Most industries map one-to-one. When this is not the

[22]This represents a vast improvement over simple measures of 'page counts', but it is still far from a perfect measure. Goldschlag and Tabarrok (2018) provide a detailed discussion of the database and its limitations, including several validation analyses that, for example, compare RegData's measure of regulatory stringency to the size of relevant regulatory agencies and the employment share of lawyers in each industry. Goldschlag and Tabarrok (2018) conclude that "the relative values of the regulatory stringency index capture well the differences in regulation over time, across industries, and across agencies."

[23]We use the mapping in tab 'NAICS codes' of file `GDPbyInd_GO_1947-2017.xls`.

Table A.2: Mapping of BEA industries to segments

BEA code	Sector/Industry	Mapped segment
	Agriculture, forestry, fishing, and hunting	Omitted
1100	Farms	Agriculture
1130	Forestry, fishing, and related activities	Agriculture
	Mining	Omitted
2110	Oil and gas extraction	Min_oil_and_gas
2120	Mining, except oil and gas	Min_ex_oil
2130	Support activities for mining	Min_support
2200	**Utilities**	Omitted
2300	**Construction**	Construction
	Durable goods manufacturing	Omitted
3210	Wood products	Dur_wood
3270	Nonmetallic mineral products	Dur_nonmetal
3310	Primary metals	Dur_prim_metal
3320	Fabricated metal products	Dur_fab_metal
3330	Machinery	Dur_machinery
3340	Computer and electronic products	Dur_computer
3350	Electrical equipment, appliances, and components	Dur_electrical
3360	Motor vehicles, bodies and trailers, and parts	Dur_transp
3360	Other transportation equipment	Omitted
3370	Furniture and related products	Dur_furniture
3390	Miscellaneous manufacturing	Dur_misc
	Nondurable goods manufacturing	Omitted
3110	Food and beverage and tobacco products	Nondur_food
3130	Textile mills and textile product mills	Nondur_textile
3150	Apparel and leather and allied products	Nondur_apparel
3220	Paper products	Nondur_paper
3230	Printing and related support activities	Nondur_printing
3240	Petroleum and coal products	Nondur_petro
3250	Chemical products	Nondur_chemical
3260	Plastics and rubber products	Nondur_plastic
4200	**Wholesale trade**	Wholesale_trade
4400	**Retail trade**	Retail_trade
	Transportation and warehousing	Omitted
4810	Air transportation	Transp_air
4820	Railroad transportation	Transp_rail
4830	Water transportation	Transp_other
4840	Truck transportation	Transp_truck
4850	Transit and ground passenger transportation	Transp_other
4860	Pipeline transportation	Min_oil_and_gas
4870	Other transportation and support activities	Transp_other
4930	Warehousing and storage	Transp_other

Table A.2: Mapping of BEA industries to segments (cont'd)

BEA code	Sector/Industry	Mapped industry
	Information	Omitted
5110	Publishing industries (includes software)	Inf_publish
5120	Motion picture and sound recording industries	Inf_motion
5130	Broadcasting and telecommunications	Inf_telecom
5140	Information and data processing services	Inf_data
	Finance and insurance	Omitted
5210	Federal Reserve banks	Omitted
5210	Credit intermediation and related activities	Omitted
5230	Securities, commodity contracts, and investments	Omitted
5240	Insurance carriers and related activities	Omitted
5250	Funds, trusts, and other financial vehicles	Omitted
	Real estate and rental and leasing	Omitted
5310	Real estate	Omitted
5320	Rental and leasing services and lessors of intangible assets	Omitted
	Professional, scientific, and technical services	Omitted
5411	Legal services	Prof_serv
5415	Computer systems design and related services	Prof_serv
5412	Miscellaneous professional, scientific, and technical services	Prof_serv
5500	**Management of companies and enterprises**	Omitted
	Administrative and waste management services	Omitted
5610	Administrative and support services	Adm_support
5620	Waste management and remediation services	Waste_mgmt
6100	**Educational services**	Educational
	Health care and social assistance	Omitted
6210	Ambulatory health care services	Health_ambulatory
6220	Hosp and nursing	Health_hospitals
6220	Hospitals	Omitted
6220	Nursing and residential care facilities	Omitted
6240	Social assistance	Health_social
	Arts, entertainment, and recreation	Omitted
7110	Performing arts, spectator sports, museums, and related activities	Arts
7130	Amusements, gambling, and recreation industries	Arts
	Accommodation and food services	Omitted
7210	Accommodation	Acc_accomodation
7220	Food services and drinking places	Acc_food
8100	**Other services, except government**	Omitted

case, we take the average number of restrictions across the given industries.

Regulatory Employment. We gather employment by occupation x NAICS x year from the BLS Occupational Employment Statistics, available here. We map NAICS codes to BEA segments through the same process as the Regulation Index. We measure regulatory-related employment in a given industry as the total number of employees with Legal or Compliance occupations (codes 23-0000 and 13-1040, respectively). For our regressions, we set regulatory employment to missing for the BEA Professional Services industry (which includes Legal Services).

A.1.3 Firm-level data.

Our firm-level data source is the CRSP-Compustat merged database, available through WRDS. We download tables Funda and Company from Compustat, and table msf from CRSP. We also download the CRSP-Compustat linking table (ccmxpf_linktable) to match the datasets. We merge the CRSP file and apply standard screens (consol = "C", indfmt = "INDL", datafmt = "STD", popsrc = "D" and curcd = "USD"). We keep firm-year observations incorporated in the USA (fic = "USA"), with non-missing year, gvkey, Q (as defined below). We require assets above \$1 million to mitigate the impact of outliers.

We use the industry codes in the Compustat Company table. NAICS codes are populated for all firms that existed after 1985, but are sometimes missing for firms that exited beforehand. We map those firms to the most common NAICS-4 industry among those firms with the same SIC code and non-missing NAICS. We also map all retired/new NAICS codes from the 1997, 2002 and 2012 versions to NAICS 2007 using the concordances in link.

We map firms to BEA industry segments using the mapping in tab 'NAICS codes' of file GDPbyInd_GO_1947-2017.xls. Firms with NAICS codes 999 are dropped because they cannot be mapped to BEA industries. For some of our tests, we supplement Compustat with the firm-level intangible capital estimates of Peters and Taylor (2016), available through WRDS.

Industry Q. We estimate firm-level Q as the ratio of market value to total assets (AT). We compute market value as the market value of equity plus total liabilities (LT) and preferred stock (PSTK), where the market value of equity is defined as the total number of common shares outstanding (item CSHO) times the closing stock price at the end of the fiscal year (item PRCC_F). When either CSHO or PRCC_F are missing in Compustat, we fill-in the value using CRSP. We cap Q at 10 and winsorize it at the 2% level, by year to mitigate the impact of outliers. Last, we aggregate firm-level Q to the industry level by taking the mean, median and asset-weighted average across all firms in a given industry-year.

Industry Concentration. We estimate import-adjusted concentration using sales from Compustat and imports from Peter Schott's website. Import data are available by HS-code x year from 1989 to 2017. HS codes are mapped to NAICS-6 industries using the concordance of Pierce and Schott (2012). We map NAICS codes to BEA segments as described above, and aggregate the industry-level.

We then define the import-adjusted market share of a given Compustat firm i that belongs to BEA industry k, as the ratio of firm sales to nominal gross output plus imports:[24]

$$s_{it}^{k} = \frac{\text{sale}_{it}^{k}}{\text{gross output}_{kt} + \text{imports}_{kt}}$$

Concentration ratios sum market shares across the top firms, by sales, in a given industry.

We aggregate concentration ratios using by taking a weighted average of industry-level concentration, with real gross output (in 2009 USD) as weights. Figure A.1 shows why weighing by real, rather than nominal quantities is preferred. As shown in the left plot (solid line), the concentration ratio weighing by nominal quantities rises quickly in the late 2000's and then falls. This is because of large variation in the price of oil, and therefore the weight of the Nondurable Petroleum industry – as shown in the right plot. Nominal output in this industry grows by a factor of 4 from 2000 to 2011, and then falls to about twice as the initial level. This leads to wide variation in the weight of this industry using nominal quantities, which pushes the aggregate CR up and then down (since this industry is relatively more concentrated). By contrast, real output and the corresponding aggregate CR remain far more stable. In fact, the series weighted by real output behaves similar to the series excluding nondurable petroleum.

A.1.4 M&A Transaction-level Data

Last, we gather M&A transaction-level data from Thomson Reuters SDC. We include only completed transactions of US-domiciled targets. SDC provides SIC codes by target. We map these codes to NAICS

[24] Because Compustat sales include exports, total sales in a given industry can exceed gross output plus imports. In that case, we define firm-level market share as the ratio of firm-sales to total Compustat sales.

using the SIC-NAICS concordance available here. We then map NAICS codes to BEA segments and aggregate by summing the transaction values.

A.2 Details on the Construction of Selected Figures

Table 1. Investment, Capital and Profits by Leaders and Laggards. Rank firms by market value. Define a firm as leader if it is the top firm in a given industry or the cumulative market value up to and including this firm is below 33% of the industry market value. Repeat the exercise for mid-performers (33-66% of MV) and the bottom 33%. Next, compute the total OIBDP, CAPX + R&D, PP&E and Capital K (including intangibles as estimated by Peters and Taylor (2016)) by year and by MV group x year. Estimate the share of a given measure – say OIBDP – as the ratio of leader OIBDP to total OIBDP in a given year. Because firms are discrete, the actual share of market value in each grouping varies from year to year. To improve comparability, re-scale shares by the ratio of 33.33% to the share of market value. Report the average across all years in a given period.

Figure 2. Net Investment, Profits and Q-Residuals Top chart plots the ratio of net investment and net buybacks to net operating surplus for the Non Financial Corporate sector. Net operating surplus is sourced directly from series NCBOSNQ027S. Net investment is defined as gross fixed capital formation minus consumption of fixed capital (series NCBGFCA027N minus NCBCFCA027N). Net repurchases equal the negative of the net incurrence of equity liabilities (series NCBCEBQ027S).

Bottom chart plots the per-period and cumulative residuals of a regression of the net investment rate for the NFB sector on Q for the NFC sector. We use the 1990 to 2001 period as a training sample and use the estimated coefficients to forecast out-of-sample after 2001. The net investment rate is defined as the ratio of Net investment (see above) to lagged capital stock. The capital stock is defined as the sum of equipment, intellectual property, residential and non-residential structures. For the NFC sector, these are series ESABSNNCB, NCBNIPPCCB, RCVSRNWMVBSNNCB and RCSNNWMVBSNNCB. For NFNC sector, ESABSNNB, NNBNIPPCCB, RCVSRNWBSNNB and RCVSNWBSNNB. Tobin's Q for the non-financial corporate sector is defined as

$$Q = \frac{V^e + (L - FA) - \text{Inventories}}{P_k K} \tag{57}$$

where V^e is the market value of equity (NCBCEL), L are the liabilities (TLBSNNCB); FA are financial assets (TFAABSNNCB); and $P_k K$ is the replacement cost of capital (sum of the four NFC capital series listed above). Inventories are based on series IABSNNCB.

Figure 3. Cumulative Capital Gap for Concentrating and Non-Concentrating Industries. We begin by identifying industries with the largest and smallest log-change in 8-firm import-adjusted concentration ratio (CR8). The top plot shows the gross output-weighted average CR8 across the corresponding industries. Right plot shows the weighted average cumulative capital gap for the corresponding industries.

We estimate the industry-level capital gap as follows. Define the net investment rate for industry k, $\frac{NI_{kt}}{K_{kt-1}}$, as Investment minus Depreciation over lagged Capital stock – all in 2009 dollars, as measured by the Chain-Type quantity indexes. Then, regresses $\frac{NI_{kt}}{K_{kt-1}}$ on the 1-year lagged median industry Q (from Compustat) over the 1990 to 2001 period. Generate the residuals ε_{kt}, and compute the cumulative gap as

$$\text{Gap}_{kt} = \varepsilon_{kt} + \text{Gap}_{kt-1} \times \left(1 - \frac{\delta_{kt}}{K_{kt-1}}\right)$$

We aggregate across industries by taking the weighted average by capital.

Figure 13. Aggregate Entry Cost Shocks vs. Regulation and M&A For regulation, estimate 3-year log-change in industry-level regulation index and winsorize at 5% level. Aggregate by taking the simple average across all industries. For M&A, simple compute the ratio of total M&A transaction values to total Gross Output across BEA industries in our sample.

B Additional Results and Figures

In this section, we present additional results and figures.

B.1 Robustness

We estimate the model along several different dimensions to check the robustness of the key estimated parameters.

1. Same ϵ_j per industry. In this case, we set $\epsilon_j = 5$ for all industries, as a test of our assumption that the transmission of shocks to industry-level outcomes is the same for all industries. This assumption is necessary for constructing the likelihood function of the model, whereby we can isolate the likelihood contribution of each industry from other industries and from the aggregate.

The results show the posterior distributions of the structural parameters are similar to our baseline estimation, with the posterior distribution of ϕ_n centered around a value of 1.7 and 10th and 90th percentiles of 1.2 and 2.3 respectively.

2. We also check the robustness of the key parameters to an estimation where the observed Q_t is matched to total industry-Q – which includes the rents of both the capital and goods-producers. [TBD]

Table A.3: Robustness of Estimated Parameters

	(1)			(2)		
Parameter	Median	10%	90%	Median	10%	90%
σ	0.4	0.4	0.4			
ϕ_n	1.7	1.2	2.3			

(1): Same $\epsilon_j = 5$ for all industries.
(2): Q_t observed matched to total industry Q.

B.2 Additional Figures

Figure A.2 plots the distribution of calibrated firm-level elasticities of substitution ϵ_j. The mean of these calibrated values is around 5, which is the value used in the estimation of the aggregate model.

Figure A.3 shows the ratio of gross operating surplus to output across industries in our sample. We calibrate the value of ϵ_j so that our model's steady-state markup is consistent with the value observed in 1993 (see also Figure A.2). This ratio is roughly constant over time for most industries.

Figure 12 plots the average entry cost shock by industry, against the industry's intangible intensity. As shown, there does not appear to be a positive relationship between the two. We find similar results using alternate measures of intangible intensity (e.g., changes, initial levels, etc).

Figure A.5 plots the response of the concentration and output when the zero lower bound binds, and when it does not. The entry cost shock lowers the natural rate, so the entry cost shock has a larger negative effect on output in the presence of the zero lower bound.

B.2.1 Aggregate Data

Figure A.6 plots the aggregate data used in estimation of the aggregate model. We describe how these series are constructed above.

B.2.2 Industry Data in Estimation

Figures A.7 through A.11 show the industry-level data used in estimation. We express the industry-level data series relative to their respective aggregate series, by subtracting a full set of time effects, one for each year and each variable. We also subtract an industry-specific fixed effect and an industry-specific trend.

Figure A.1: Aggregated Concentration Series

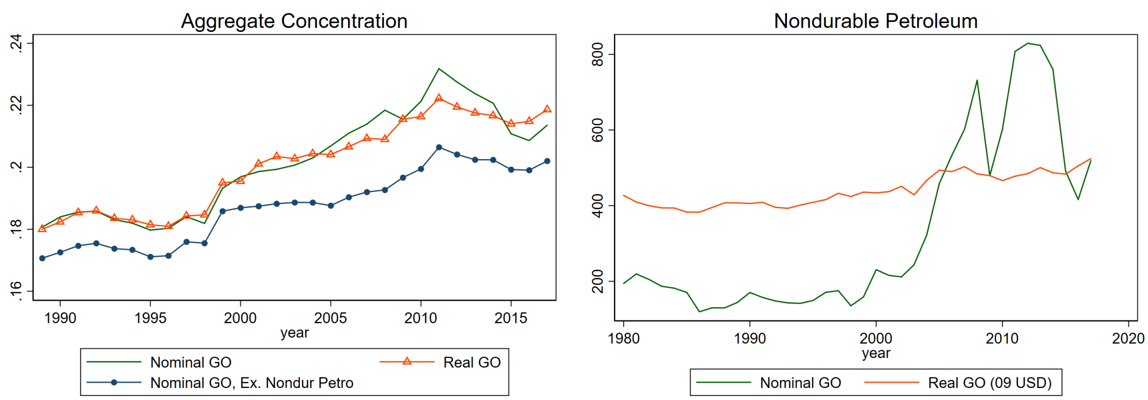


Figure A.2: Distribution of Calibrated Firm-Level Elasticity of Substitution

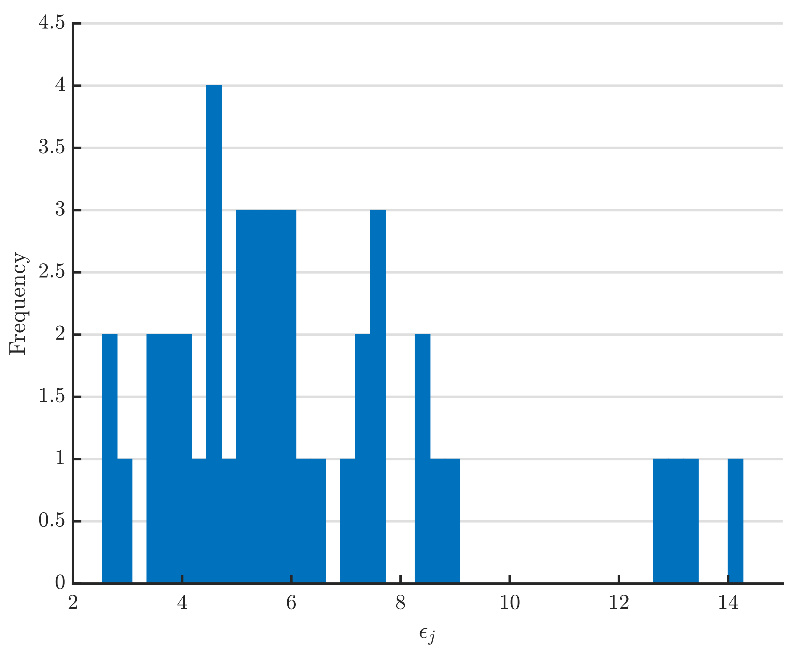


Figure A.3: Industry Gross Operating Surplus to Output Ratio

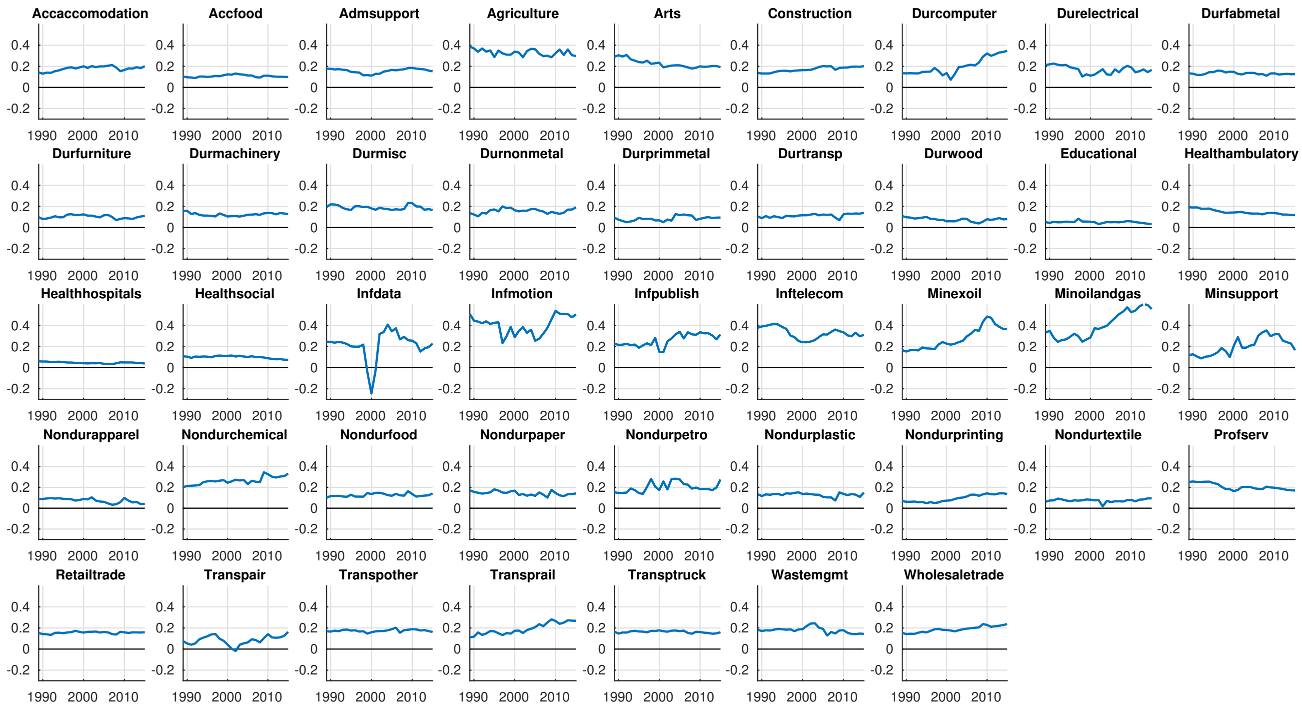
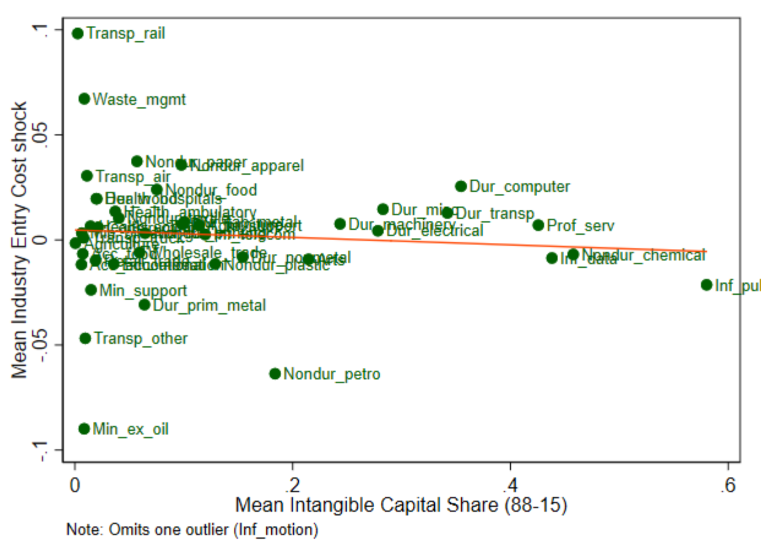


Figure A.4: Industry Entry Cost Shocks vs. Intangible Intensity



Notes: Annual data. Entry cost shocks estimated by the model. Intangible intensity based on the BEA's FAT tables.

Figure A.5: Aggregate Entry Cost Shocks at the Zero Lower Bound

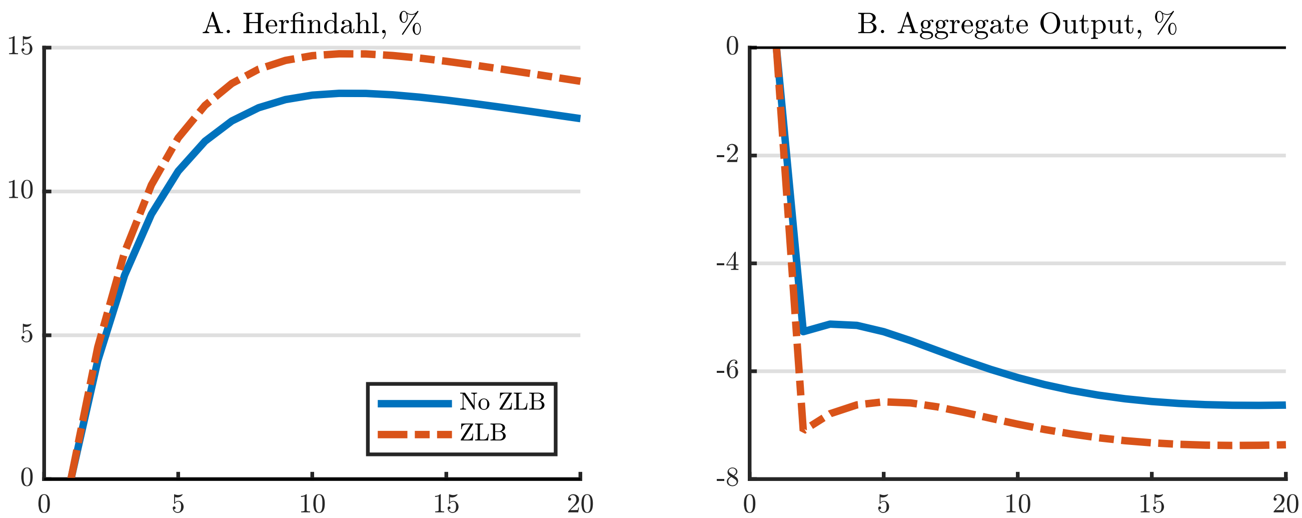


Figure A.6: Aggregate Data in Estimation

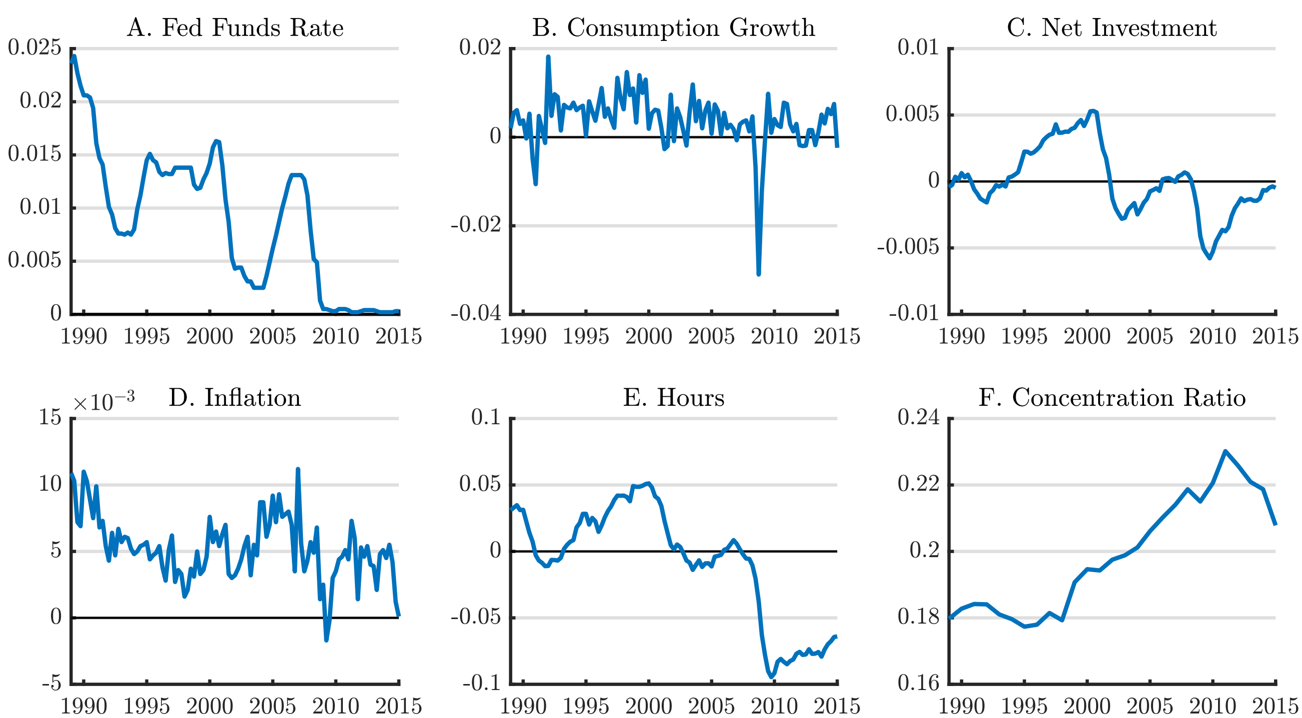


Figure A.7: Industry Data in Estimation, Nominal Output

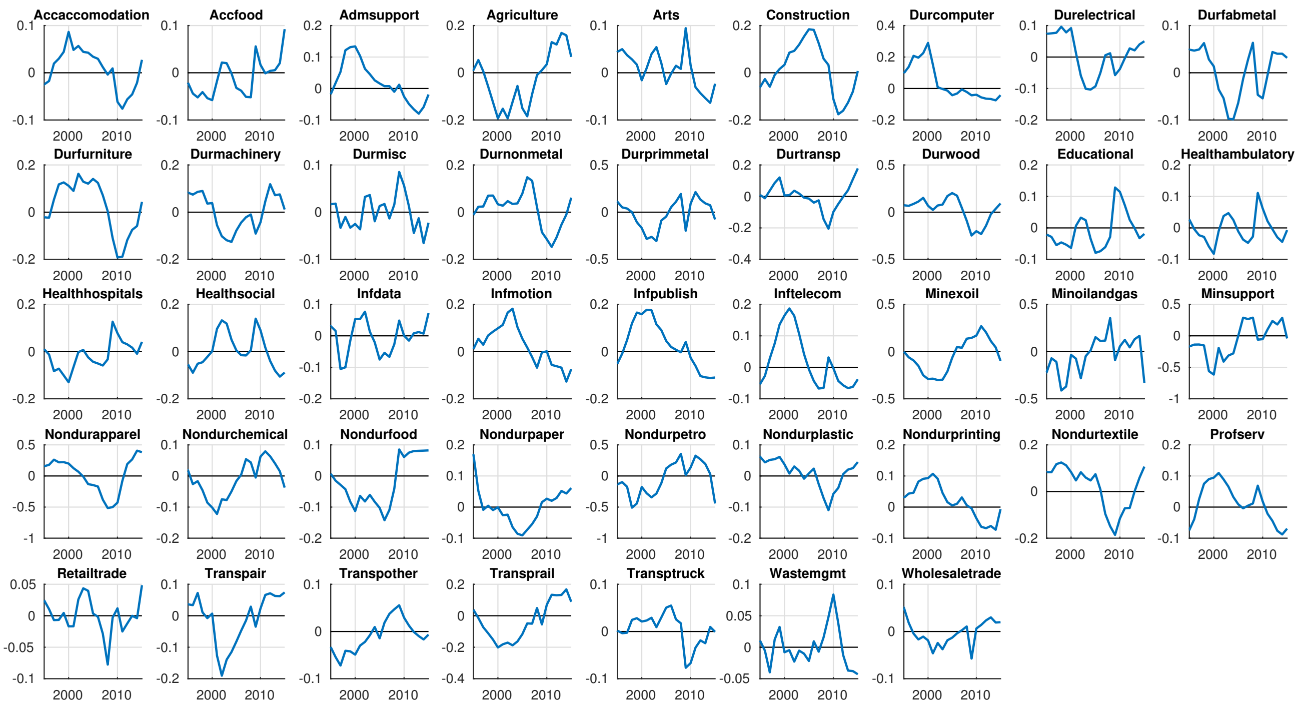


Figure A.8: Industry Data in Estimation, Capital

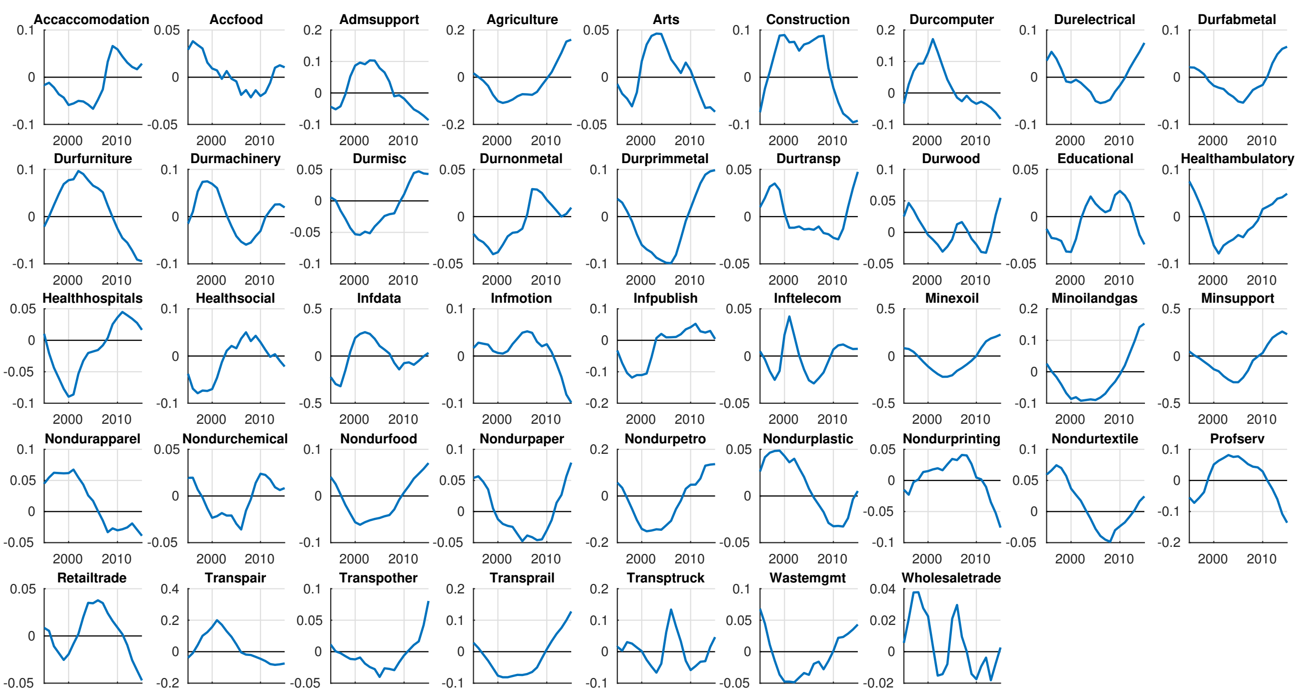


Figure A.9: Industry Data in Estimation, Concentration Ratio

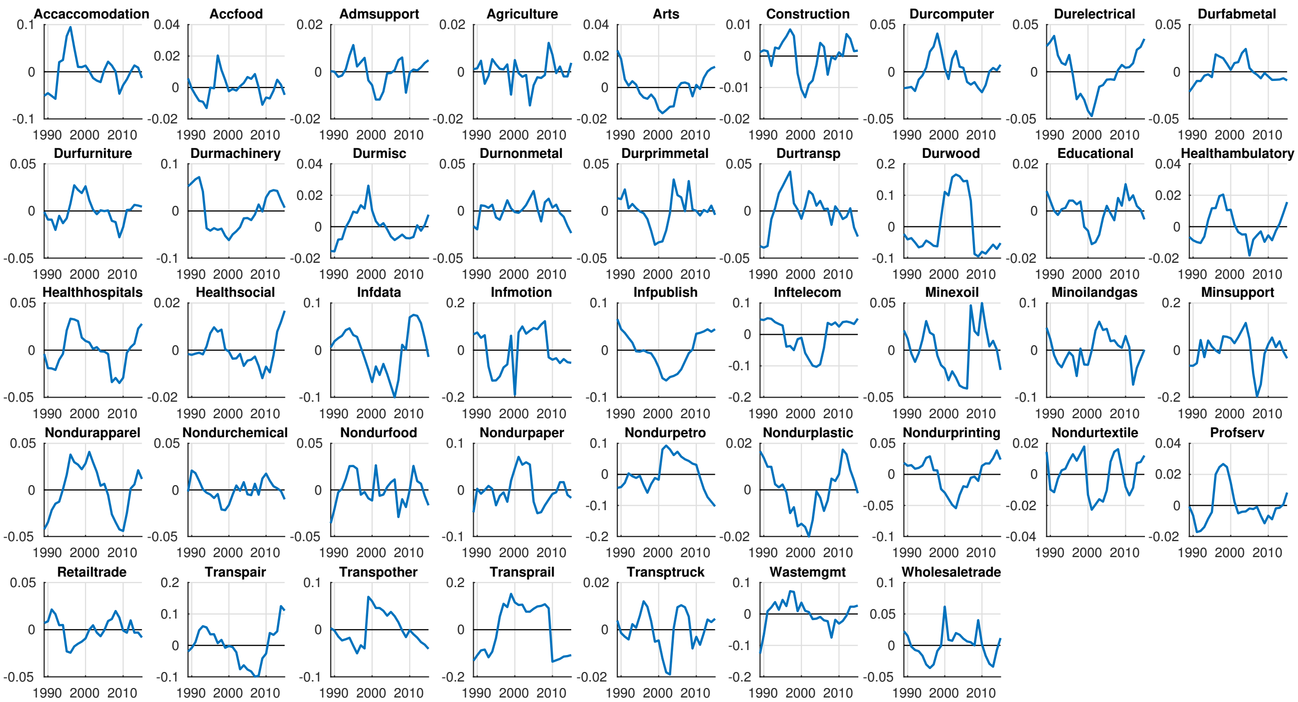


Figure A.10: Industry Data in Estimation, Q

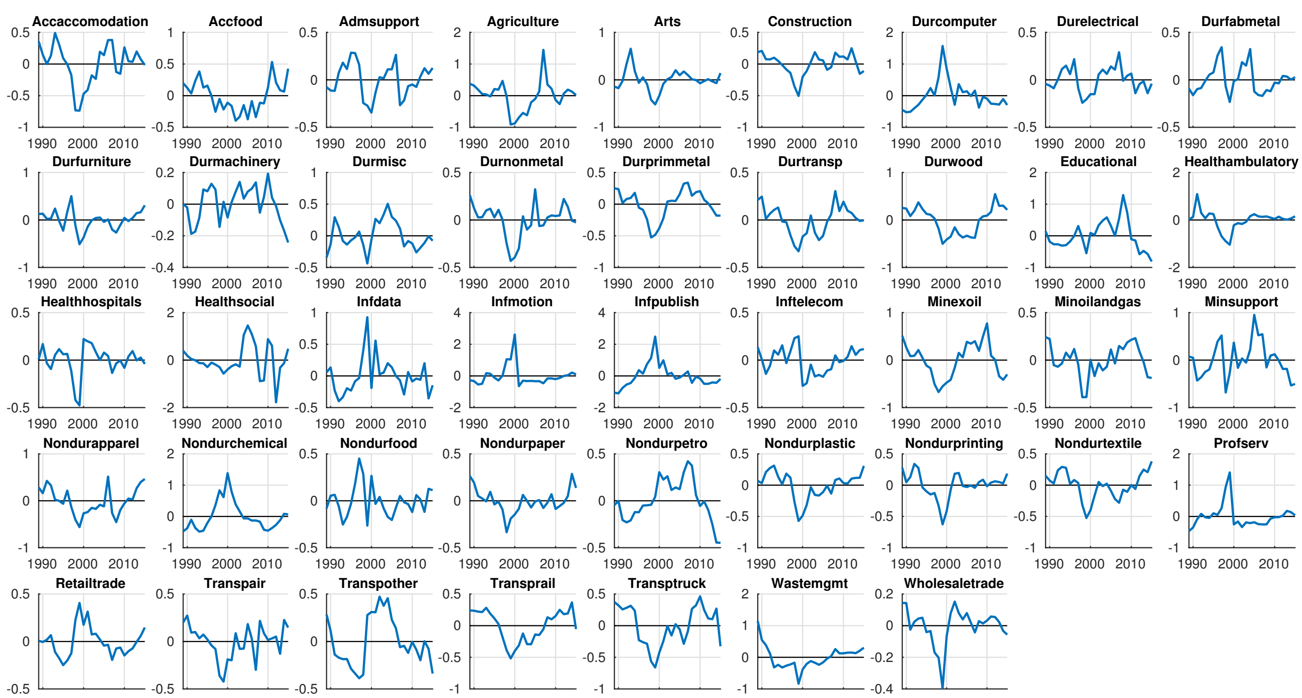


Figure A.11: Industry Data in Estimation, Price Inflation