

Entry Costs and the Macroeconomy*

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Abstract

We combine a structural model with cross-sectional micro data to identify the causes and consequences of rising concentration in the US economy. Using asset prices and industry data, we estimate realized and anticipated shocks that drive entry and concentration. We validate our approach by showing that the model-implied entry shocks correlate with independently constructed measures of entry regulations and M&As. We conclude that entry costs have risen in the U.S. over the past 20 years and have depressed capital and consumption by about seven percent.

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JEL classifications: E2, E4, E5, L4.

1 Introduction

Four stylized facts characterize the U.S. economy in recent decades. (i) U.S. industries have become more concentrated, while (ii) profit margins have increased; (iii) business dynamism – including firm entry rates and the share of young firms in economic activity – has fallen; and (iv) business investment has been low relative to measures of profitability, funding costs, and market values.¹ While these stylized facts are well established (Decker, Haltiwanger, Jarmin and Miranda, 2014; 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

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¹See Section 2 for additional details on these facts.

instance, Furman (2015) and CEA (2016) argue that the rise in concentration suggests “economic rents and barriers to competition”, while Autor et al. (2017b) 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 variation in any of these variables. The second challenge is that the macroeconomic implications of declining competition are difficult to analyze outside a fully specified model. As a result, both the empirical and the theoretical literature are limited: little has been done to identify the causes of the four trends empirically; and most macroeconomic models 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 using a structural model together with micro 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.

At the industry level, 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 followed and/or accompanied by an increase in output and investment. Anticipated demand (or productivity) shocks can thus explain why we see more activity 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,

²Finally trade and globalization can explain some of the same facts (Feenstra and Weinstein, 2017; Impullitti et al., 2017). Foreign competition can lead to an increase in domestic concentration and a decoupling of firm value from the localization of investment. We control for exports and imports in our analyses. Foreign competition is significant for about 3/4 of the manufacturing sector, or about 10% of the private economy. 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 Covarrubias et al. (2019) for detailed discussions and references.

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 useful way to estimate some important parameters of the model, such as the elasticity of entry to Tobin’s Q .

Our second 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 several steps, as we explain below, but the broad intuition is relatively simple. Using Bayesian estimation methods, our model recovers annual industry-level entry cost shocks – which can then be compared to *independent* measures of entry regulations and antitrust activities computed from the micro-data. 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. In the aggregate, entry shocks are large and important for matching time series. They explain 15% of the variation in investment, 29% of the variation in output and about half of the variation in concentration.

The last contribution of the paper is methodological but it turns out to be empirically important. We specify the likelihood function for the data panel and estimate the model 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), which uses a Kalman filter and information about the expected durations of the ZLB to back out the other shocks that drive the model (including productivity, discount rate and risk premia). While the ZLB – and monetary policy more generally – might seem like a separate issue, we show that it plays an important role in our estimations for two reasons. First, the ZLB depresses the economy and therefore impacts entry and concentration. Failing to properly model the ZLB would over-estimate the magnitude and impact of aggregate entry costs. Second, 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 increasing barriers to entry have had a significant impact on macro-economic dynamics over the past 30 years. For instance, absent the decrease in competition since 2003, consumption and the capital stock would be about 7 percent higher.

Literature. Our approach introduces several new ways to examine the relationship between firm entry, competition, and the macroeconomy. This has been the subject of a long, but predominantly empirical literature in the U.S. Bernard et al. (2010) study the contribution of product creation and destruction to aggregate output. They estimate that product creation by both existing firms and new firms accounts for 47 percent of output growth in a 5-year period. 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. Davis and Haltiwanger (2019) emphasize the role of the housing market for explaining the decline.

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. Autor et al. (2017b) 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 and find a large increase in mark-ups. Barkai (2017), on the other hand, estimates the required return on capital directly and finds a moderate increase in excess profits. Both estimates are controversial, however, so we do not use them directly in our analyses (Basu, 2019; Syverson, 2019; Covarrubias et al., 2019).

Methodologically, our paper is related to general equilibrium models of imperfect competition. Bilbiie et al. (2012) study how entry affects the propagation of business cycles in a standard RBC model with technology shocks. Endogenous entry costs generate variations in the stock market price of investment, which in turn affect entry decisions. This is consistent with our model. We build on their approach, and use data on Tobin’s Q to back out a time-series of entry costs. Relatedly, Cacciatore and Fiori (2016) estimate that reducing entry costs in Europe to the level observed in the U.S. in the late 1990s would have increased investment by 6%. Cacciatore et al. (2017) study the impact product market reforms at the ZLB. Lincoln and McCallum (2018) and Maggi and Felix (2019) study the effects

³Furman (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).

of entry costs for international trade. Edmond et al. (2019) decompose the welfare costs of markups into misallocation across firms, inefficient entry, and an equivalent uniform output tax.

Eggertsson et al. (2018), Corhay et al. (2018) and Kozeniauskas (2018) are perhaps the closest papers to our work. Eggertsson et al. (2018) take entry as exogenous and model a time-varying elasticity of substitution between intermediate goods to study the ability of time-varying market power to explain a number of broad macroeconomic trends. Corhay et al. (2018) develop an innovation-based endogenous growth model with aggregate risk premia and endogenous markups; and use it to decompose the rise in Q into revised growth expectations, rising market power, and changes in risk premia. Corhay et al. (2018) conclude that declines in competition explain a large portion of the increase in Q . Albeit with a different structure, our model also features endogenous entry decisions sensitive to future demand expectations. In contrast to Corhay et al. (2018), however, we model industries separately. This allows us to identify the key parameters of the model and to connect entry costs to explicit measures of entry regulations. Kozeniauskas (2018) takes a different approach. He uses a general equilibrium model of occupational choice to study the contribution of four explanations to the decline in entrepreneurship: changes in wages driven by skill-biased technical change; changes in technology facilitating the expansion of large firms; changes in fixed costs (which combine sunk entry costs and per-period operating costs); and changes in demographics. In line with our findings, he concludes that increasing fixed costs are the main explanation for the decline in entrepreneurship.

Our paper is also related to a long literature in IO that studies the evolution of industries when entry costs are endogenous and may be influenced by incumbents. Stigler (1971) focuses on regulation and argues that “as a rule, regulation is acquired by the industry and is designed and operated primarily for its benefit.” Sutton (1991, 1997) studies how incumbents use marketing and R&D to increase entry costs – and therefore limit the number of firms in an industry. Djankov et al. (2002) document large differences in entry costs across countries, and link them to levels of corruption, and Mukoyama and Popov (2014) develop a political economy model in which incumbent firms lobby for higher entry barriers that can raise concentration.

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 decades. Section 3 presents our benchmark model. We start from a standard DSGE model in which we allow for the possibility that the ZLB constraint on short term nominal rates binds. Section 4 discusses how we solve our model and form its likelihood function. Section 5 verifies that our estimated entry cost shocks correlate with independently constructed measures of entry regulation and M&A; and Section 6 presents the aggregate implications of our model.

2 Four Facts About Entry, Concentration, Profits and Investment

We begin with four stylized facts that guide our analyses.⁴

Fact 1: Profits and Concentration have Increased. Figure 1 shows the ratio of Corporate Profits to Value Added for the U.S. Non-Financial Corporate sector, along with the cumulative weighted average change in 8-firm concentration ratio in manufacturing and non-manufacturing industries. As shown, both series increased after 2000. These patterns are pervasive across industries as shown by Grullon et al. (2016).

Fact 2: Entry Rates have Fallen. Figure 2 plots aggregate entry and exit rates from the Census BDS. Entry rates began to fall in the 1980s and accelerated after 2000. Exit rates have remained stable. This is true at the aggregate and industry-level, and remain when controlling for profits or Q as shown in Gutiérrez and Philippon (2018).

Fact 3: Investment is Low Relative to Profits and Q . The top chart in Figure 3 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

⁴See Appendix A.2 for additional details on the construction of these results.

relative to Q since the early 2000's. By 2015, the cumulative under-investment is large at around 10% of capital. The decline appears across all asset types, notably including intangible assets (Covarrubias et al., 2019).

Fact 4: The Lack of Investment Comes from Concentrating Industries. Figure 4 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 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. This result highlights why it is critical to consider investment alongside concentration.

3 Model

To explain the drivers behind 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.⁵ We use data at the industry-level on concentration and profitability to estimate the elasticity of firm entry to changes in Q . Those estimates are then used to understand the aggregate consequences of changes in entry costs.

Many of the features of our model are standard to the New Keynesian literature (see for example Smets and Wouters, 2007; Gali, 2008), and we focus on the new and non-standard additions to the basic framework, namely: (i) firm entry, (ii) estimated industry-specific shocks to expected demand, and (iii) monetary policy at the ZLB. The Appendix describes the remaining features of our model.

3.1 Firm Entry

Consider an industry indexed by j where goods-producing firms hire capital, labor, and intermediate goods for production, and make pricing decisions. Potential entrants pay an entry cost to become active producers in the subsequent period.⁶ Let $N_{j,t}$ be the number of firms. The number of firms active at time $t + 1$ is

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

⁵This assumption simply allows us to maintain the standard Q -equation and the standard Phillips curve.

⁶Our focus is on the time variation of entry costs. See Bilbiie et al. (2006) for a discussion of corrective taxes.

Each active firm disappears with probability δ_n , while $n_{j,t}$ is the number of entrants that become active in period $t + 1$. An exogenous exit rate is consistent with the data, as reported by Lee and Mukoyama (2018). Entry requires a fixed input $\kappa_{j,t}$ produced competitively in industry with a convex cost function, so that the input price $p_{j,t}^e$ is

$$p_{j,t}^e = (\kappa_{j,t} n_{j,t})^{\phi_n}. \quad (2)$$

Free entry then requires that

$$p_{j,t}^e \kappa_{j,t} \geq \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}, \quad (3)$$

where Λ_t is the household's pricing kernel and $V_{j,t}$ is the value of the goods-producing firm given by

$$V_{j,t} = \text{Div}_{j,t} + (1 - \delta_n) \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}, \quad (4)$$

where $\text{Div}_{j,t}$ are real dividends. Equation (3) holds with equality as long as $n_{j,t} > 0$, which is the case in our simulations. Our assumption of convex entry costs slows entry during booms, which helps match the volatility of entry rates and their relationship to asset prices. This convexity can have multiple interpretations, from diminishing quality in managerial ability (Bergin et al., 2017) to congestion effects at firm creation (Jaef and Lopez, 2014) – perhaps due to a limited supply of Venture Capital needed to finance and monitor entrants (Loualiche, 2016). The entry cost $\kappa_{j,t}$ is subject to industry-specific and aggregate shocks:

$$\kappa_{j,t} = \kappa + \zeta_{j,t}^\kappa + \zeta_t^\kappa, \quad (5)$$

where the industry and aggregate-level shocks are autoregressive processes

$$\zeta_{j,t}^\kappa = \tilde{\rho}_\kappa \zeta_{j,t-1}^\kappa + \tilde{\sigma}_\kappa \epsilon_{j,t}^\kappa \quad (6)$$

$$\zeta_t^\kappa = \rho_\kappa \zeta_{t-1}^\kappa + \sigma_\kappa \epsilon_t^\kappa. \quad (7)$$

In this model entry costs regulate the link between entry of new firms and the market value of incumbents, therefore they capture not only technological costs, but also administrative costs and regulatory barriers, and deterrence by incumbents.

Finally, when we map our model to the data we take into account that Tobin's Q reflects not only the usual capital adjustment costs but also monopolistic rents. An empirical feature of the data is

that capital is not perfectly mobile across industries. Formally, we assume that there are industry-specific capital providers, so that an industry's total Q combines the rents of goods-producers and capital-producers $Q_{j,t}^k$, all measured at the end of the period

$$Q_{j,t} = Q_{j,t}^k + \frac{(1 - \delta_n)\mathbb{E}_t[\Lambda_{t+1}V_{j,t+1}]}{P_t K_{j,t+1}}. \quad (8)$$

The elasticity of the number of entrants $n_{j,t}$ to $Q_{j,t}$ depends on the parameter 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.

3.2 Industry-Specific Demand Shocks

Demand System We use a standard nested CES demand system. The final good is a composite of industry-level outputs $Y_{j,t}$ aggregated by a perfectly competitive final goods firm:

$$Y_t = \left[\int_0^1 (D_{j,t} Y_{j,t})^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}}, \quad (9)$$

where σ is the elasticity of demand across industry-level goods, and $D_{j,t}$ is an industry-level demand shifter described in more detail below. The price index for Y_t is P_t , defined as $P_t = \left(\int_0^1 P_{j,t}^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}$, where $P_{j,t}$ is the price index of industry j . As a rule, we define real variables (i.e., scaled by the GDP deflator P_t) unless there are nominal rigidities. So, for instance, $R_{j,t}^k$ is the real rental rate of capital in industry j , while W_t is the nominal wage and $p_{i,j,t}$ is the nominal price set by firm i in industry j . Under (9), the demand curve faced by firms in an industry is

$$Y_{j,t} = D_{j,t} \left(\frac{P_{j,t}}{P_t} \right)^{-\sigma} Y_t. \quad (10)$$

Firms' output (indexed by i) is aggregated into the industry output

$$Y_{j,t} = \left(\int_0^{N_{j,t}} y_{i,j,t}^{\frac{\epsilon_j-1}{\epsilon_j}} di \right)^{\frac{\epsilon_j}{\epsilon_j-1}} = y_{j,t} (N_{j,t})^{\frac{\epsilon_j}{\epsilon_j-1}}, \quad (11)$$

where, with some abuse of notation, we denote by $y_{j,t}$ the average firm output in industry j , $N_{j,t}$ is the number of active (producing) firms in industry j at time period t and ϵ_j is the elasticity of substitution across firms within the industry. We see here the impact of product variety on productivity. The

industry price index is an aggregate of firm level price choices:

$$P_{j,t} = \left(\int_0^{N_{j,t}} p_{i,j,t}^{1-\epsilon_j} di \right)^{\frac{1}{1-\epsilon_j}}. \quad (12)$$

The term $D_{j,t}$ is an industry-level demand shifter, with $d_{j,t} = \log D_{j,t}$ following the process:

$$d_{j,t} = (1 - \tilde{\rho}_d)d_j + \tilde{\rho}_d d_{j,t-1} + \tilde{\sigma}_d \epsilon_{j,t}^d. \quad (13)$$

We estimate transitory shocks to $d_{j,t}$, or $\epsilon_{j,t}^d$, to help account for variation in relative industry output over time.

Beliefs and Expected Demand We also estimate shocks to *beliefs* about d_j , the “average” 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 and valuations observed in a number of industries before 2000, and is a useful instrument for identifying the responsiveness of firm entry to profitability, as parameterized by ϕ_n . The presence of noisy entry is documented in several studies. Doms (2004), for example, looks at 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.⁷

One explanation for noisy entry is that there is variation 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).⁸ 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

⁷See also Hogendorn (2011).

⁸According 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.

entry, especially because firm entry increases precisely during periods of high-growth such as the late 1990's (Asturias et al., 2017).

3.3 Monetary Policy at the ZLB

To close the model, we specify a policy rule for the central bank, taking into account the ZLB on nominal interest rates. We assume that monetary policy follows a standard Taylor rule for the nominal interest rate

$$\tilde{r}_t^* = -\log(\beta) + \phi_i \tilde{r}_{t-1}^* + (1 - \phi_i) (\phi_p \pi_t^p + \phi_y (\ln Y_t - \ln Y_t^F)) + \phi_g \ln \left(\frac{Y_t / Y_{t-1}}{Y_t^F / Y_{t-1}^F} \right) + \sigma_i \epsilon_t^i, \quad (14)$$

where π_t^p is price-level inflation, Y_t^F is the flexible price level of output, ϵ_t^i is a monetary policy shock, and the actual (log) short rate is constrained by the ZLB

$$\tilde{r}_t = \max(0; \tilde{r}_t^*). \quad (15)$$

At the ZLB, we allow for forward guidance as an extension of the ZLB duration beyond that implied by fundamentals and the shocks. That is, we allow, but do not impose, that the policy rate be extended beyond the duration implied by shocks, in line with the optimal policy prescription of Eggertsson and Woodford (2003). We discipline the expected lower bound durations with empirical measures, as discussed in the estimation section.

3.4 Remaining Model Elements

The rest of the model is standard and the equations are in the Appendix. The model features capital producers in each industry who accumulate capital subject to convex adjustment costs to maximize market value. Their problem gives rise to the Q -theory of investment, with net investment rising in line with Tobin's Q – the market value of the firm relative to the size of the capital stock. Goods-producers in each industry operate a Cobb-Douglas production function and face a price-setting problem under Calvo nominal rigidities, giving rise to industry-specific Phillips curves. The household sector is standard, with workers belonging to unions that face Calvo-style nominal wage rigidities.

In addition to industry-specific shocks to demand beliefs, we also model, at the industry-level, transitory shocks to demand, productivity, the valuation of corporate assets, the inflation equation, and entry costs. At the aggregate-level, we model shocks to productivity, the valuation of corporate

assets, the Phillips curve, the household’s discount factor, the monetary policy rule, and entry costs. The rich set of shocks will help account for the industry and aggregate data.

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, the persistence and size of transitory shocks, as well as the parameters of the monetary policy rule.

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 and the monetary policy rule are estimated. We then use the estimated aggregate model to conduct our aggregate experiments on the role of barriers to 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 US Business sector.⁹ We set δ_n , the exogenous firm exit rate, to 0.09/4 to match the average annual exit rate of Compustat firms.¹⁰ We calibrate the quarterly capital 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 parameters, ϵ_j , to match the gross operating surplus to output ratio in 1993 from the BEA industry series.¹¹ 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 profit levels in those industries.¹² We follow Edmond et al. (2019) and set

⁹Investment and output data are available for 63 granular industry groupings from the BEA. We omit 7 industries in the Finance, Insurance and Real Estate sectors; as well as 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.

¹⁰We use Compustat firms to focus on the exit of large firms.

¹¹Given that the model’s implied steady-state gross operating surplus to output ratio changes as σ changes, we recalibrate the values of ϵ_j accordingly. Figure A.5 in the Appendix plots the distribution of ϵ_j across industries in our baseline calibration.

¹²For most industries, the gross operating surplus to output ratios are stable and do not change much over time, as we show in the Appendix.

ρ , the elasticity of substitution between labor and intermediate goods, to 0.5.

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%.

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 the beliefs d_j about average demand in industry j . We normalized the “true” values to $d_j = 0$, but we allow agents to have different beliefs during the internet bubble, from 1995 to 1999. With aggregate-level data, we estimate the parameters of the monetary policy rule, and 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. The Appendix provides a complete description of the data and definitions.

- We measure the concentration ratio as the share of sales by the top 8 firms in each BEA industry using Compustat. To account for time-varying coverage in Compustat as well as foreign competition, we adjust for total industry-level gross output using the BEA GDP by Industry accounts, and for imports using the data of Pierce and Schott (2012).¹³ In the model, all firms are identical, so that the Herfindahl index is $\int (y_{i,j,t}/Y_{j,t})^2 di = \int (y_{i,j,t}/N_{j,t}y_{j,t})^2 di = 1/N_{j,t}$ and the top k firms have a share of $k/N_{j,t}$.
- 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.¹⁴ In our baseline, we match the observed values of Q to

¹³We use Compustat as opposed to Census concentration because it is available over a longer period under a consistent segmentation. One downside of using Compustat is that all of the activity of multi-industry firms is mapped to each firm’s primary industry, as opposed to the corresponding industries. This is not an issue for Census concentration measures, where each establishment is mapped to the corresponding industry. To validate our use of Compustat, we validate that Compustat and Census concentration measures exhibit similar behavior in unreported tests: they have 65 to 70% correlation in levels and 40 to 50% in 5-year changes.

¹⁴Gutiérrez 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

the Q of goods-producers.¹⁵

- We measure nominal output and prices at the industry-level using the BEA’s GDP-By-Industry accounts, and investment and capital stocks at the industry-level using the BEA’s Fixed Assets Tables.

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 ZLB between 2009Q1 and 2015Q1, we use data from the New York Federal Reserve Survey of Primary Dealers, following Kulish et al. (2017).

4.4 Solution Method

The first challenge in our estimation 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 ZLB. We discuss each challenge in this section. The next section discusses how we use our approximation below to form the likelihood function for estimation.

Solution Method for Subjective 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. We use the adjective “true” to simplify the discussion but this is of course a semantic distinction. Our model is entirely consistent with agents receiving unobserved noisy signals about future demand. Under this interpretation the late 1990s was simply a period of high optimism. Denote the true demand regime which is driving the observables as

$$\mathbf{A}\mathbf{x}_t^j = \mathbf{C} + \mathbf{B}\mathbf{x}_{t-1}^j + \mathbf{D}\mathbb{E}_t\mathbf{x}_{t+1}^j + \mathbf{F}\epsilon_t^j, \quad (16)$$

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 . Agents in the model, however, believe in an alternative demand regime. They think that the industry’s

¹⁵We 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.

law of motion follows the * matrices

$$\mathbf{A}^* \mathbf{x}_t^j = \mathbf{C}^* + \mathbf{B}^* \mathbf{x}_{t-1}^j + \mathbf{D}^* \mathbb{E}_t \mathbf{x}_{t+1}^j + \mathbf{F}^* \epsilon_t^j. \quad (17)$$

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

$$\mathbf{x}_t^j = \mathbf{J}_t + \mathbf{Q}_t \mathbf{x}_{t-1}^j + \mathbf{G}_t \epsilon_t^j. \quad (18)$$

In periods when beliefs $\mathbb{E}_t \mathbf{x}_{t+1}^j$ accord with regime (16), the solution is the standard time-invariant solution

$$\mathbf{x}_t^j = \mathbf{J} + \mathbf{Q} \mathbf{x}_{t-1}^j + \mathbf{G} \epsilon_t^j. \quad (19)$$

Instead, in periods when beliefs $\mathbb{E}_t \mathbf{x}_{t+1}^j$ are formed with (17) 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 (17). Substituting these beliefs $\mathbb{E}_t \mathbf{x}_{t+1}^j$ into (16) and rearranging gives

$$\tilde{\mathbf{Q}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} \mathbf{B} \quad (20)$$

$$\tilde{\mathbf{G}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} \mathbf{F} \quad (21)$$

$$\tilde{\mathbf{J}} = [\mathbf{A} - \mathbf{D}\mathbf{Q}^*]^{-1} [\mathbf{C} + \mathbf{D}\mathbf{J}^*] \quad (22)$$

For our time-varying representation (18), 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 and Forward Guidance. Our second computational challenge is to approximate the dynamics of our model where the policy rate is subject to the ZLB. We do so following the approach of Guerrieri and Iacoviello (2015) and Jones (2017). The logic of the solution is similar to the time-varying approximation (18) that we use for estimating demand beliefs. We define two additional regimes, one for when the ZLB does not bind, and one for when the ZLB binds. At each point in time the ZLB 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 ZLB 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 (18).

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 (18) and the industry and aggregate data together. However, the nonlinearities induced by the ZLB 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, which we describe here.

Let \mathbf{x}_t^j 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:

$$\mathbf{x}_t^j = \mathbf{J} + \mathbf{Q}\mathbf{x}_{t-1}^j + \mathbf{G}\epsilon_t^j + \mathbf{J}_t^a + \mathbf{Q}_t^a\mathbf{x}_{t-1}^* + \mathbf{G}_t^a\epsilon_t^*. \quad (23)$$

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:

$$\mathbf{x}_t^* = \mathbf{J}_t^* + \mathbf{Q}_t^*\mathbf{x}_{t-1}^* + \mathbf{G}_t^*\epsilon_t^* \quad (24)$$

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

Intuitively, under (23), for an industry j , aggregate shocks and the ZLB do not change the response of firms in that industry to its own history of idiosyncratic shocks. Under this, letting $\mathbf{x}_t = \int \mathbf{x}_t^j dj$ denote the economy-wide average of the industry-level variables, the deviation of industry-level variables from their economy-wide averages,

$$\hat{\mathbf{x}}_t^j = \mathbf{x}_t^j - \mathbf{x}_t, \quad (25)$$

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

$$\hat{\mathbf{x}}_t^j = \mathbf{J} + \mathbf{Q}\hat{\mathbf{x}}_{t-1}^j + \mathbf{G}\epsilon_t^j, \quad (26)$$

where we use the assumption $\int \epsilon_t^j dj = 0$, that industry-level shocks have zero mean in the aggregate. We then use the representation in (24) and (26) 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.

To ensure that the industry data is consistent with (25), 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.

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.¹⁶ We choose wide priors for the parameters. The elasticity across industry-level goods, σ , is estimated to be around 0.4, which is reasonable for broad classes of goods, and consistent with the trade literature. The value of ϕ_n is around 1.6, with a 10th and 90th percentile of 1.2 and 2.1, 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 0.99, while the persistence of the technology shocks is around 0.95.

For the demand beliefs, 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.

¹⁶We compute two independent chains of length 500,000 and discard the first 20% of each chain. The convergence of the posterior distributions is analyzed in the Appendix.

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 $d_j = 0$.¹⁷ Some industries are estimated to have low expected demand; for example, rail transport has an estimated expected steady-state demand of around -0.4. In addition, some durable manufacturing industries are estimated to have low beliefs about demand, such as durable non-metal, durable primary metals, and durable miscellaneous manufacturing, which have estimated steady-state demands of around -0.15. Agriculture, waste management, and healthcare-related industries 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. The information data industry is estimated to have beliefs about demand of around 1.4, significantly higher than its true value of 0. This industry includes IBM, Google and Facebook. Durable computing and professional and administrative services (which includes computer systems design and related services) also exhibit high estimated beliefs about demand. The former includes Dell, Hewlett-Packard, and Motorola; while the latter includes large IT service providers such as NEC Corp, Fujitsu and Accenture. We explore the implications of these estimated demand parameters in the next section.

Aggregate Estimates. The estimates of the monetary policy rule are presented in Panel A of Table 2. The values of the coefficients are similar in magnitude to those estimated in other studies (see for example Justiniano et al., 2010). 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 shocks to entry costs, TFP and to the valuation of corporate assets – risk premia shocks – are key drivers of aggregate variables. In reduced-form, the shock to the valuation of corporate assets has similar implications as the marginal efficiency of investment shocks that are found to be key drivers of business cycles in Justiniano et al. (2010). As discussed in that paper, shocks to the marginal efficiency of investment, in the presence of frictions that drive an endogenous wedge between the marginal product of labor and the marginal rate of substitution, are able to generate the comovement of hours and consumption observed in the data.

Aggregate entry cost shocks are found to explain a significant amount of the variation of hours

¹⁷The full estimates of beliefs about demand that are held between 1995 and 2000 are shown in Figure A.3 in the Appendix.

(about 19%), the natural rate (about 55%), and most of the Herfindahl index (about 97%) at business cycle frequencies. Unconditionally, the Herfindahl and the number of firms in the economy in our model is largely explained by technology shocks (46%), entry cost shocks (46%), and risk premia shocks (7%). We also find that entry cost shocks explain a large fraction of the variation in hours (21%), aggregate output (13%), consumption (10%), and the natural rate (50%), at the infinite horizon. As shown in counterfactual simulations in the final section, during our sample period 1989 to 2015, we find an important role for firm entry cost shocks in explaining investment, consumption, and the natural interest rate. Intuitively, similar to technology shocks, entry cost shocks can generate the comovement between consumption, hours, and investment present in the data, as well as comovement between inflation and the Fed Funds rate, while the use of data on concentration is a powerful way to identify the shock in the data (Figure A.1 in the Appendix plots the aggregate-level impulse responses).

4.7 Industry Implications

We next examine the implications of our estimates for industry-level variables. We show that about 10% of the variation in relative industry concentration ratios between 1995 and 2000 can be explained by firm entry driven by firms' 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 30% of the relative variation in the capital stock between 1995 and 2000 is accounted for by demand belief shocks, with the remainder of the variation mostly accounted for by risk premia shocks.

We first present the industry-level impulse responses to industry-level shocks. We focus on 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 $\phi_n = 1.6$ implies that entry into the industry is fairly gradual. 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). This illustrates one of the main identification issues in the literature: demand shocks create negative correlations between output and

investment on the one hand, and concentration on the other even though concentration is not causing the changes in real activity.

Figure 5b plots the impulse response of industry-level observables following a one standard deviation shock to entry costs. Profits rise, entry drops and concentration increases. The Herfindahl index rises by about 1%, while industry-level real output falls by just over 0.1%. Figure 5c plots the impulse response to a one standard deviation productivity shock, which we find temporarily lowers prices and goods-producers' Q_t , reduces firm entry, and raises real output. These responses to productivity shocks of course depend on the elasticity of substitution σ , which is less than one in our estimation across broad industry categories.

We next explore what the estimated shocks imply for the industry-level variables. In Figure 6 we focus on the information data industry. Panel A plots the path of the Herfindahl index used in estimation and the path under the estimated demand beliefs only (without stochastic shocks). Panel B plots the path of the capital stock used in estimation under demand beliefs only. 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, 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 is accounted for by the shock to beliefs about steady-state demand.

For all industries, the expected demand shock explains about 10% of the change in firm concentration. Figure 7 shows the impact of expected demand shocks on concentration and investment. We switch off all other shocks and simulate industry dynamics with only expected demand shocks. Panel A shows the predicted change in Herfindahl against the observed change in Herfindahl from 1995 to 2000. Across all industries, the slope of the regression line is 0.1 and the correlation is 0.4. For the capital stock, the slope is 0.3 and the correlation is 0.85. There are two take-aways from this figure. First, expected demand shocks are large and volatile in the late 1990s, and this gives us much more power to identify the model's parameters than any time series evidence. Second, empirical models that do not take these shocks into account could be significantly biased.

5 Explaining Entry Cost Shocks

Our estimation results suggest that entry costs play an important role in explaining the behavior of key aggregate and industry-level variables. In this section, we seek to validate our estimates. We show that the entry cost shocks recovered from the model are correlated with empirical proxies of barriers to entry not used in the estimation – namely regulations and M&A activity.¹⁸

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. Easing of M&A restrictions – as documented by Kwoka (2015) – allow incumbents to consolidate and potentially increase barriers to entry. M&A may increase for other reasons, including demand shocks and technological change (Andrade et al., 2001) so we would not expect our estimates to explain all the time variation in M&A activities.

We use Thomson Reuters SDC to measure M&A activity and RegData 3.1 (Al-Ubaydli and McLaughlin, 2015) for regulations.¹⁹ 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.²⁰ Figure 8 compares the median rise in regulation (across industries) with the decline in firm entry rates. Regulatory restrictions increased relatively slowly until 1995, when the growth accelerated. The timing of the increase in regulation is consistent with the hypothesis that regulation hurts entry, but the trends

¹⁸It is worth noting that regulation and M&A affect more than entry costs: regulations likely increase fixed costs in addition to entry costs, while M&A likely affects competitive dynamics for incumbents as well as entrants. Our tests, therefore, seek to establish a relationship between these measures and entry costs, not to comprehensively study the impact of regulation or M&A on firm dynamics. More broadly, one might worry that the estimated entry costs are driven by technological change. Figure A.8 plots the average entry cost shock by industry against the industry’s intangible intensity. There does not appear to be a positive relationship between the two.

¹⁹RegData relies on machine learning and natural language processing techniques to construct measures of regulatory stringency at the industry level. 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, including comparisons of regulation indices to the size of 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) suggest 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. Last, we focus on national regulations given the use of national data, even though State and Local government also have regulatory responsibilities. It is hard to summarize the scale of state and local government regulation or its growth over time, but anecdotal evidence suggests a similar increase. Occupational licensing, for example, increased from less than 5% in the 1950s to 29% in 2008 (Kleiner and Krueger, 2013) – in large part because of greater prevalence of licensing requirements at the State-level.

²⁰In 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.

could also be explained by some common factor. We therefore look across industries, which experienced widely different paths of regulation. Figure 10, for example, shows that restrictions nearly tripled in Chemical and Non-metal Manufacturing (the two industries with the fastest increase), yet remained largely stable in Food Manufacturing and Mining (the two industries with the lowest increase).

To test whether regulation and M&A explain the rise in entry costs, we compare the model-implied structural shocks with our empirical measures of Regulation and M&A – as illustrated in Figure 10 for two industries where the entry shocks are large. The top panel shows the growth of regulatory restrictions in the Nondurable Paper Manufacturing industry. The model captures well the broad cyclical variations but not always the timing. For instance, the large increase in regulatory restrictions happens around 1997 but entry declines most strongly in 1999. Unfortunately the data does not allow us to build proxies for implementation lags. The bottom panel of figure 10 shows M&A activity in the Air Transportation industry. Once again the model captures well the broad cyclical variations but not always the timing. The pattern aligns with a controversial merger wave that included Delta-Northwest (2008), United-Continental (2010), Southwest-AirTran (2011) and American-US Airways (2014). As expected the M&A series seems to lead the model-implied shocks. The timing and persistence of the shocks is sometimes difficult to compare between the model and the data. For instance, a large merger can increase concentration for several years if there is no subsequent entry. In our model, this shows up as a persistent entry shock, but in the data it is a one time merger.

In figure 10 we selected two industries with large shocks to illustrate how we can compare the model and the data and to emphasize important caveats. Let us now turn to a more systematic analysis. Table 4 confirms the significant connection between our model-implied shocks and our direct empirical proxies across all industries. We regress $\zeta_{j,t}^k$ on measures of regulation and M&A at the industry-level. All regressions include industry and year fixed effects. Column 1 includes the full sample 1989-2015 and uses the regulation indices from RegData. Columns 2 and 3 consider our alternate measure 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.²¹ Columns 5 and 6 replicate column 1 and 4, adding a measure of M&A activity.²²

Overall, we find support for the key predictions of our model across industries and over time. Our

²¹In 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.

²²Figure A.2 in the Appendix plots the aggregate entry-cost shock ζ_t^k against measures of regulation and M&A activity.

stylized model cannot explain all the variation in the micro data but the results allow us to validate our approach and give us confidence for the macro simulations that follow.

6 Firm Entry and the Decline in Investment

In this section, we use our estimated model to study the macroeconomic consequences of entry costs. We focus in particular on investment, output and monetary policy. In our main counterfactual, we set entry costs to zero from 2003 onwards and we use the model to simulate the economy. Our findings suggest that entry cost shocks account for much of the increase in aggregate concentration and that they have large effects on aggregate investment, the natural interest rate, and the stance of monetary policy. In our counterfactual exercise, we find that absent entry cost shocks, the aggregate Herfindahl index would have been about 15 percentage points lower by 2015 and the capital stock would have been about 7% higher.

The first step in our approach is to obtain the smoothed shocks that generate the aggregate data.²³ With those shocks, we construct counterfactual series by setting the entry cost shocks to zero from 2003Q1 on. The presence of the occasionally binding ZLB during 2009 to 2015 complicates the interpretation of this counterfactual because, in practice, the ZLB can be binding because of the shocks themselves (including the entry cost shock) or because of monetary policy actions taken during this period (which, in principle, could be in response to the effects of entry cost shocks). For this reason, in assessing the effect of entry cost shocks, we construct two comparable counterfactual series: (i) a counterfactual where we remove the contribution of stimulatory forward guidance during the ZLB period, and (ii) a counterfactual with entry cost shocks set to zero from 2003 onwards and the nominal interest rate subject to the occasionally binding ZLB. Our approach to removing the contribution of forward guidance is to allow the ZLB durations to react endogenously to the identified shocks; the difference between these endogenous durations and the durations used in the estimation (and in deriving the shocks) quantifies the extent of lower-for-longer forward guidance at each point in time.

Figure 11 plots the simulated paths of the Herfindahl and the Fed Funds rate without entry cost shocks. Panel A plots the Herfindahl index in the data and in the counterfactual. There is substantially

²³For 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.4 in the Appendix. We also show in the Appendix that our implied series for entry rates matches the decline in entry rates observed in Census data and documented by a number of papers discussed in the Introduction. Furthermore, to obtain the model's estimated shocks, we use the sequence of expected ZLB durations that are used in the estimation.

more entry in the counterfactual and the simulated Herfindahl is about 15 points lower without entry cost shocks by the end of the sample. Panel B shows that the Fed Funds rate would have lifted off by the second half of 2013 without entry costs. Panel B also shows the path of the Fed Funds rate if we take away the ZLB constraint. The ZLB seems to be a significant constraint on monetary policy, particularly around 2013 where we estimate that the Fed would have lowered the rate by almost 2 percentage points in 2013. This observation is consistent with estimates of the shadow interest rate (see Wu and Xia, 2016).

Next, we explore what our model predicts for investment and consumption. Panel A of Figure 12 plots the log of the capital stock, and panel B the log of consumption both in the data and in our two simulations. Without entry costs consumption and the capital stock would be almost 7.5% higher by 2015. We conclude that entry cost shocks have a significant effect on aggregate quantities and that modeling monetary policy during the ZLB is crucial to determine the aggregate effects of these shocks.²⁴

Entry costs also have a large impact on labor income and on the labor share. In Panel A of Figure 13, we plot the filtered series for labor income against the counterfactual without entry shocks from 2003 onwards. By the end of 2015, labor income is almost 20 percent higher in the counterfactual. For the labor share, we construct the contribution of entry cost shocks by looking at the difference between our counterfactual without forward guidance and with all shocks, and our counterfactual without entry cost shocks and forward guidance. We plot this contribution in Panel B of Figure 13 against the filtered measure of the labor share implied by our data series. We find that entry cost shocks explain about half of the decline in the labor share.

The aggregate effect of the identified decline in firm entry can be separated into the direct channel caused by fewer firms investing, and an indirect channel caused by the binding ZLB 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 ZLB, we plot in Panel C of Figure 13 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. The simulation illustrates the important role that firm entry has had in explaining movements in the natural rate. Comparing the counterfactual against the data-implied natural rate, our estimates imply that the positive entry cost shocks caused the annualized

²⁴Removing forward guidance causes the level of capital to fall by 0.6 percentage points by 2012 and by 1.1 percentage points by 2015. For consumption, removing forward guidance causes consumption to fall by 1.6 percentage points by 2012, and by 0.7 percentage points by 2015 as the forward guidance stimulus unwinds

natural rate to fall by about an additional 3 percentage points by the end of 2010.

7 Conclusions

Entry has decreased in the U.S. 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.

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Table 1: Assigned Parameters

Parameter	Value	Description	Source/Target
ν	2	Inverse labor supply elasticity	
β	$0.97^{1/4}$	Discount factor	
θ_p	2/3	Price setting Calvo probability	Average price contract of 3Q
θ_w	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	0.025	Capital depreciation rate	
δ_n	0.09/4	Exogenous firm exit rate	Average annual % firm exit
ρ	0.5	EOS between $\ell_{i,j,t}$ and $m_{i,j,t}$	Edmond et al. (2019)
ψ	0.6	Weight on labor in composite $h_{i,j,t}$	
ϵ_j	2.5 to 14.3	Industry substitution elasticity	$GOS_j/\text{Nominal Output}_j$ in 1993

Table 2: Estimated Parameters

Parameter	Prior				Posterior			
	Dist	Median	10%	90%	Mode	Median	10%	90%
A. Structural Parameters								
σ	N	1.0	0.3	1.6	0.424	0.423	0.398	0.447
ϕ_n	N	1.5	0.8	2.1	1.513	1.552	1.192	2.027
ϕ_r	B	0.7	0.6	0.9	0.782	0.786	0.755	0.815
ϕ_p	N	2.0	1.7	2.3	1.512	1.559	1.344	1.802
ϕ_g	N	0.2	0.1	0.3	0.175	0.170	0.066	0.281
ϕ_y	N	0.2	0.1	0.3	0.260	0.260	0.198	0.332
B. Industry Shock Processes								
$\tilde{\rho}_q$	B	0.5	0.2	0.8	0.002	0.002	0.001	0.005
$\tilde{\rho}_\kappa$	B	0.5	0.2	0.8	0.083	0.099	0.043	0.170
$\tilde{\rho}_d$	B	0.5	0.2	0.8	0.991	0.990	0.985	0.993
$\tilde{\rho}_a$	B	0.5	0.2	0.8	0.947	0.946	0.939	0.953
$\tilde{\rho}_e$	B	0.5	0.2	0.8	0.054	0.079	0.030	0.163
$10 \times \tilde{\sigma}_q$	IG	0.6	0.3	1.9	3.078	3.076	3.015	3.138
$\tilde{\sigma}_\kappa$	IG	0.6	0.3	1.9	0.316	0.314	0.277	0.350
$10 \times \tilde{\sigma}_d$	IG	0.6	0.3	1.9	0.055	0.057	0.044	0.074
$\tilde{\sigma}_a$	IG	0.6	0.3	1.9	0.064	0.065	0.060	0.070
$10 \times \tilde{\sigma}_e$	IG	0.6	0.3	1.9	0.431	0.429	0.397	0.457
C. Aggregate Shock Processes								
ρ_z	B	0.5	0.2	0.8	0.984	0.984	0.978	0.989
ρ_b	B	0.5	0.2	0.8	0.909	0.908	0.883	0.932
ρ_e	B	0.5	0.2	0.8	0.826	0.823	0.777	0.857
ρ_q	B	0.5	0.2	0.8	0.938	0.938	0.923	0.952
ρ_κ	B	0.5	0.2	0.8	0.599	0.592	0.529	0.644
$100 \times \sigma_z$	IG	0.6	0.3	1.9	1.038	1.037	0.954	1.138
$100 \times \sigma_b$	IG	0.6	0.3	1.9	0.125	0.137	0.109	0.170
$100 \times \sigma_e$	IG	0.6	0.3	1.9	0.117	0.116	0.105	0.130
$100 \times \sigma_q$	IG	0.6	0.3	1.9	0.120	0.122	0.102	0.147
$100 \times \sigma_i$	IG	0.6	0.3	1.9	0.158	0.155	0.137	0.178
$10 \times \sigma_\kappa$	IG	0.6	0.3	1.9	0.960	0.970	0.882	1.076

Table 3: Variance Decomposition of Aggregate Variables

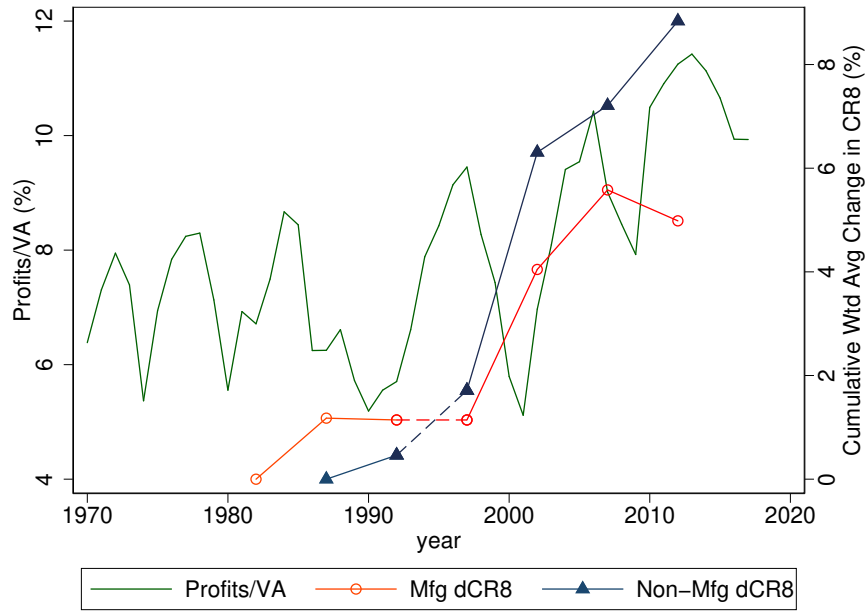
Shock Variable	Technology	Preference	Markup	Risk Premia	Policy	Entry Cost
A. 8 Quarter Horizon						
Fed Funds Rate	0.4	14.1	34.3	22.3	28.1	0.8
Output	76.6	0.3	0.8	1.5	0.2	20.6
Consumption	70.0	7.1	5.6	3.0	1.0	13.2
Net Investment	44.6	10.5	1.7	33.6	1.8	7.8
Employment	16.7	3.1	43.9	7.2	10.5	18.6
Inflation	1.8	16.8	15.4	32.8	26.0	7.1
Herfindahl	0.8	0.1	0.0	2.0	0.0	97.1
Natural Rate	0.2	18.8	0.0	25.6	0.0	55.4
B. Unconditional						
Fed Funds Rate	3.9	13.8	31.6	23.1	26.1	1.6
Output	81.7	0.7	0.1	4.2	0.0	13.2
Consumption	83.9	1.5	0.7	3.4	0.1	10.4
Net Investment	54.6	7.4	1.2	26.2	1.2	9.3
Employment	16.0	3.0	41.1	9.5	9.8	20.7
Inflation	1.7	17.3	15.1	34.6	24.6	6.6
Herfindahl	46.0	1.1	0.1	6.8	0.0	46.0
Natural Rate	4.2	19.0	0.0	27.3	0.0	49.6

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. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	$\zeta_{j,t}^k$					
	(1) All	(2) Post-02	(3) Post-02	(4) Post-02	(5) All	(6) Post-02
$\Delta \log(\text{Reg Index}_{t-2,t-1}^j)$	0.044** (0.014)	0.047* (0.017)			0.044** (0.014)	
$\Delta \log(\text{Reg Emp}_{t,t+1}^j)$			0.031* (0.013)			
Mean(L.dRegIndex,F.dRegEmp)				0.038** (0.009)		0.033** (0.010)
$\log(\text{M\&A}_{j,t})(2Y \text{ MA})$					0.047* (0.021)	0.087* (0.037)
Ind FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
R2	.051	.091	.085	.095	.057	.11
Observations	837	358	358	358	837	358

Figure 1: Concentration and Profits



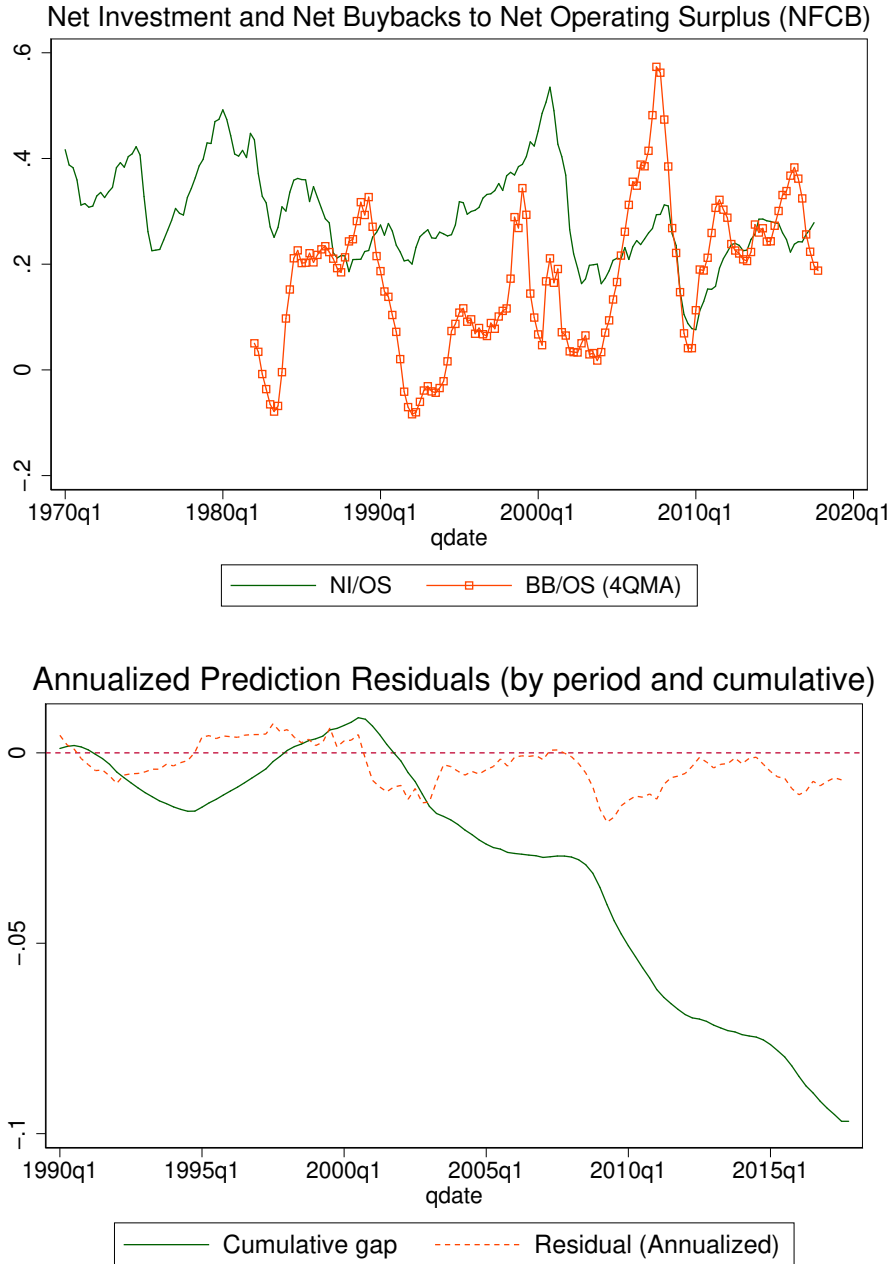
Notes: Solid line plots ratio of After Tax Corporate Profits with inventory valuation adjustment and capital consumption adjustment to Value Added for the U.S. Non-Financial Corporate sector (series W328RC1A027NBEA and NCBG-VAA027S, respectively). Annual data from the Financial Accounts of the United 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. Change from 1992 to 1997 imputed from Autor et al. (2017a) given the change in industry classification from SIC to NAICS. 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: Firm Entry and Exit Rates



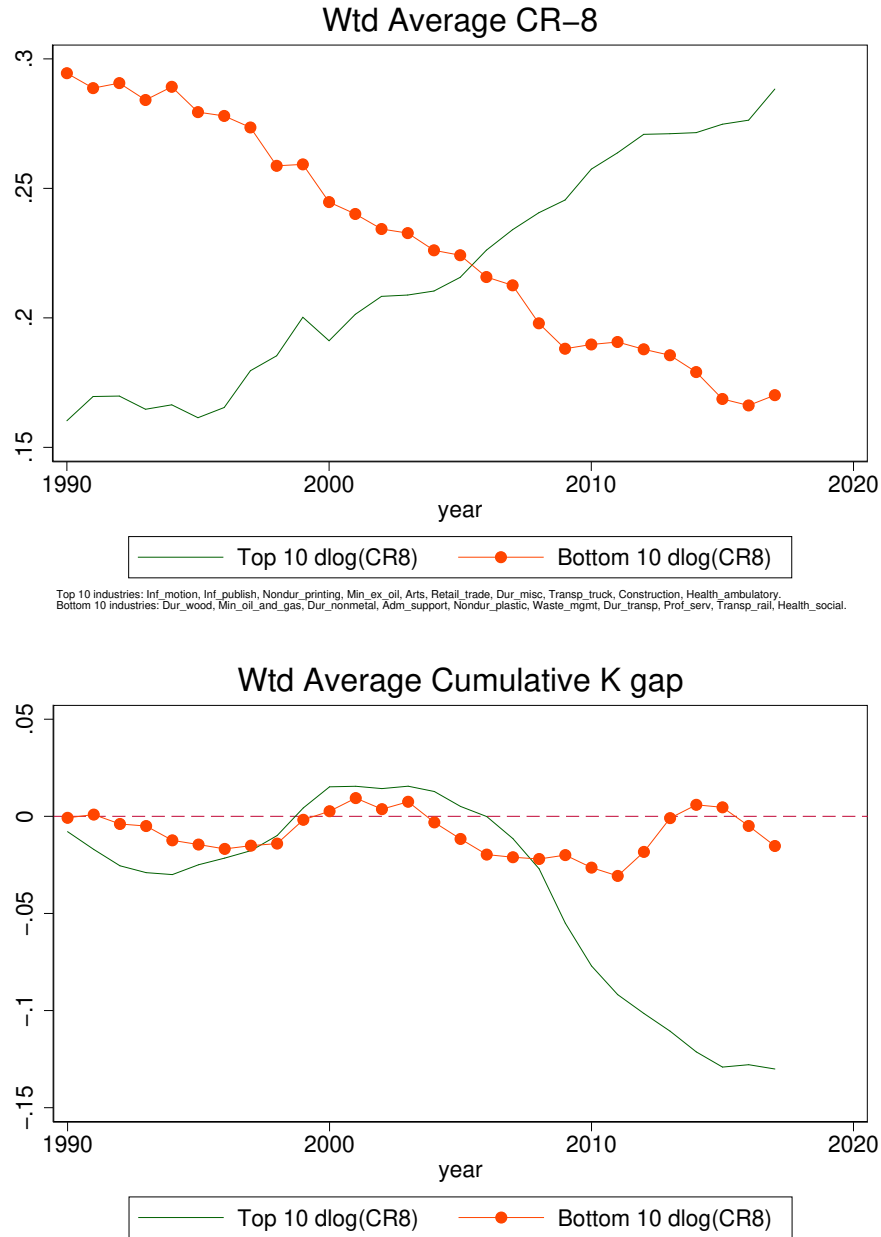
Source: Census BDS

Figure 3: 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.

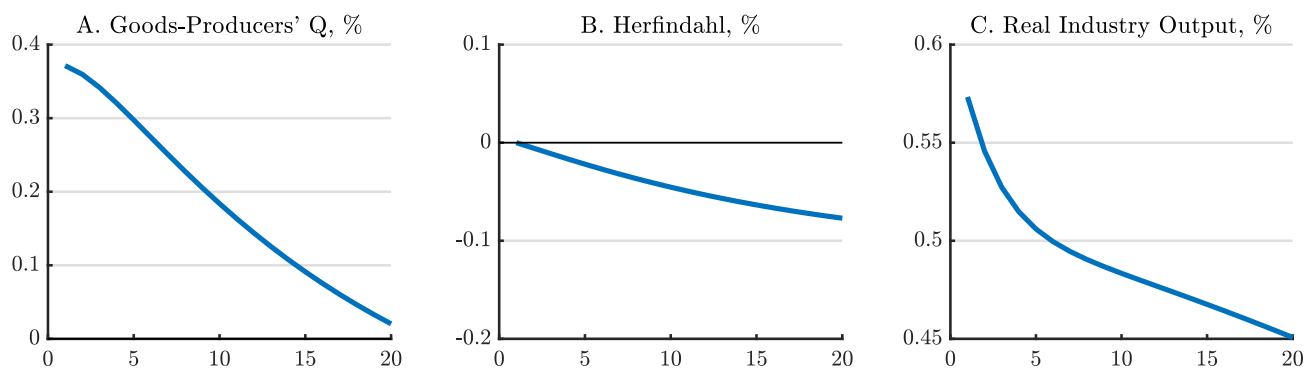
Figure 4: Cumulative Capital Gap for Concentrating and Non-Concentrating Industries



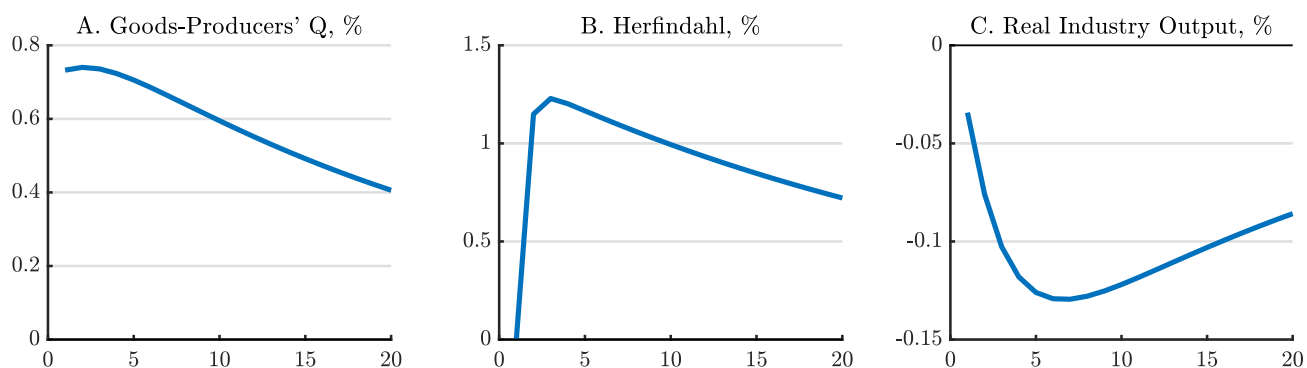
Notes: Annual data. Top plot shows the weighted average import adjusted 8-firm Concentration Ratio (CR8) for the 10 industries with the largest and smallest log-change in import-adjusted CR8 between 2000 and 2017. Bottom plot shows the cumulative implied capital gap (as a percent of capital stock) for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

Figure 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

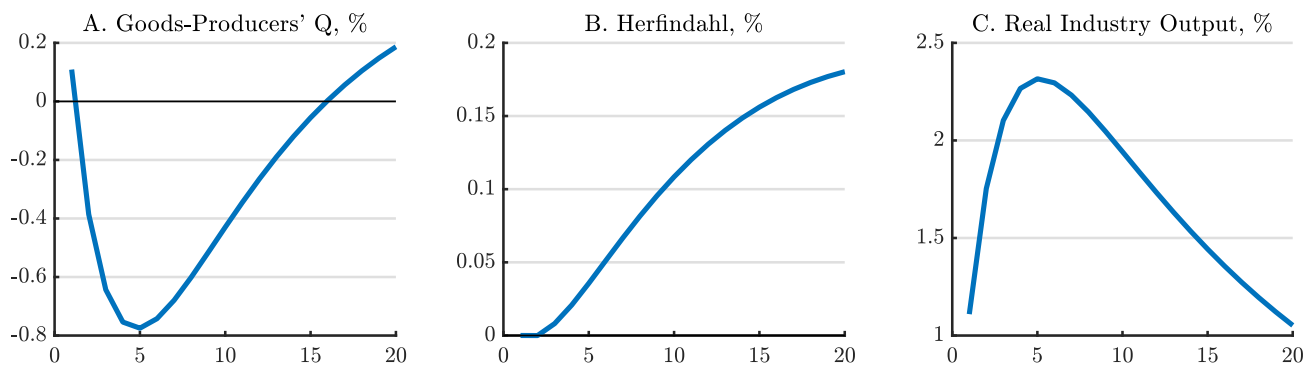


Figure 6: Information Data Industry, Identified Demand Belief Shock

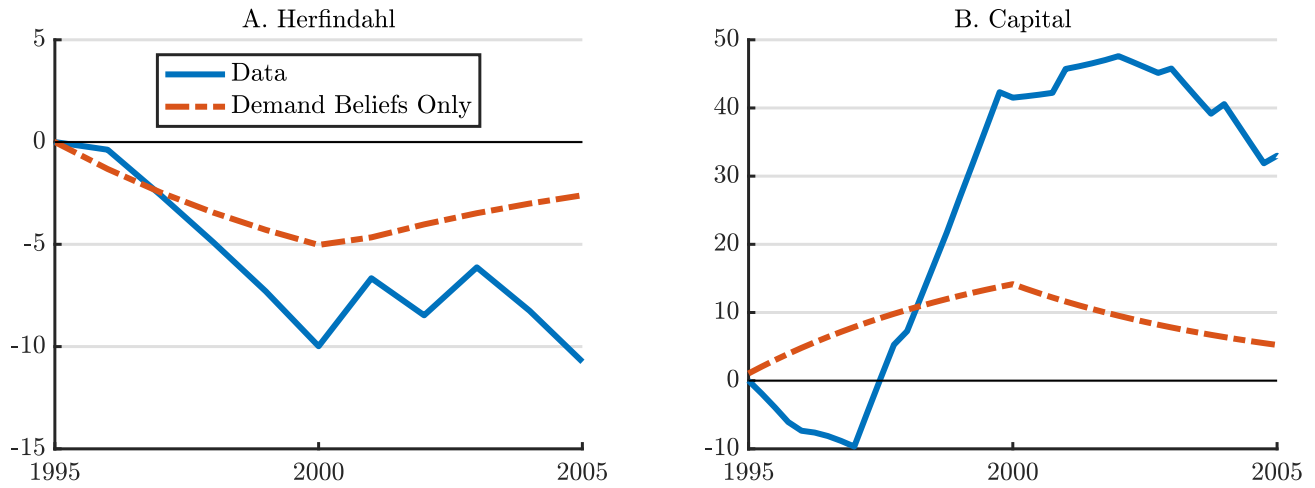


Figure 7: Industry Counterfactual, Demand Belief Shocks Only

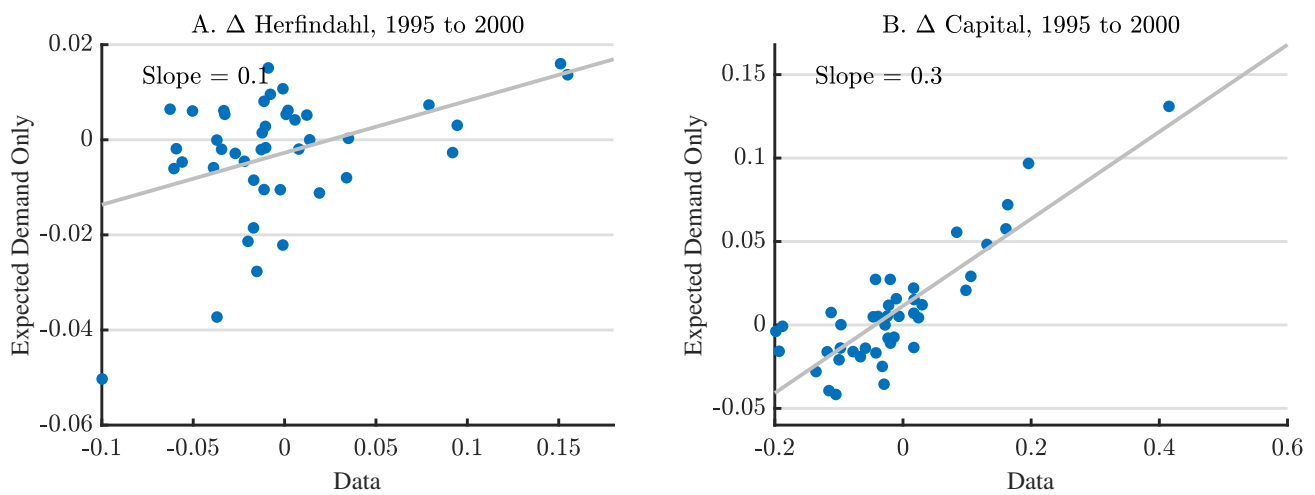
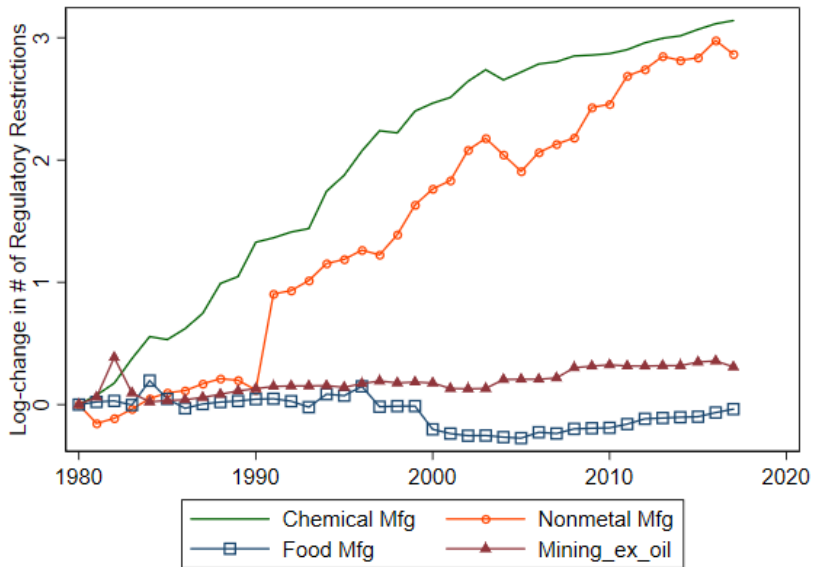


Figure 8: Regulation Index and Firm Entry Rate



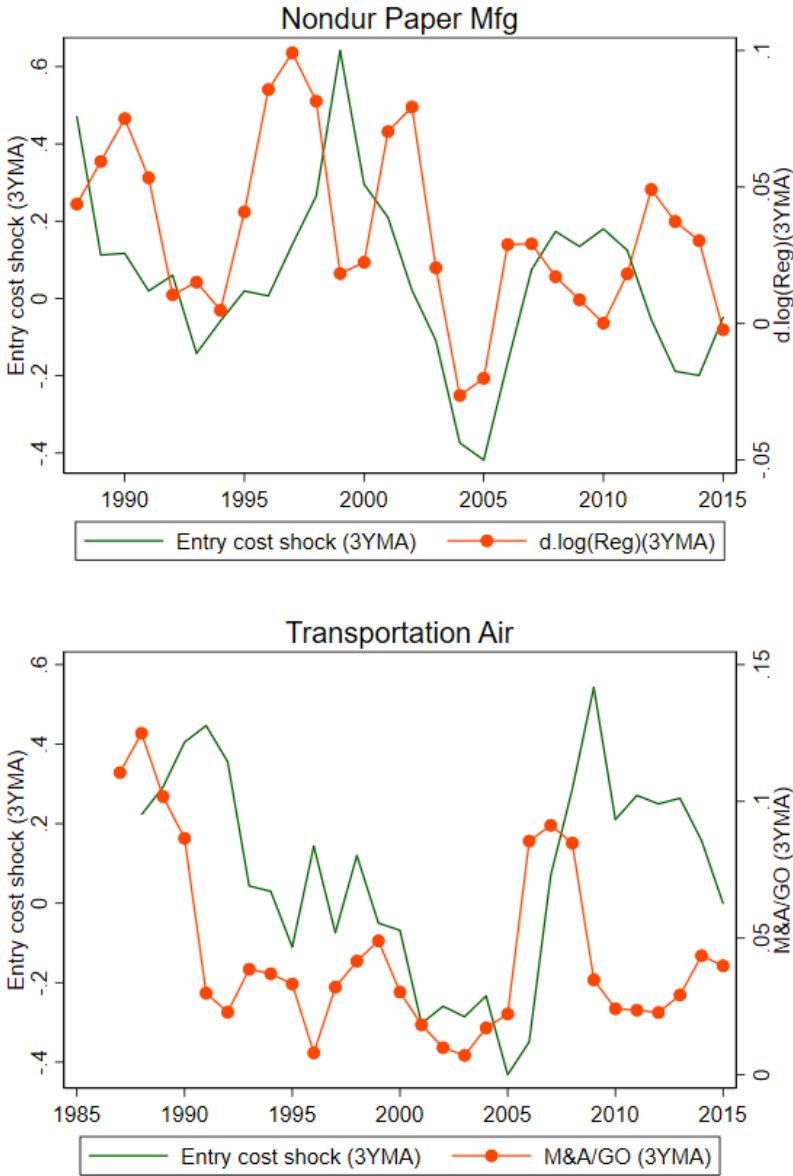
Source: Firm entry rates from Census' Business Dynamics Statistics. Regulatory restrictions from RegData.

Figure 9: Changes in Industry-level Regulatory Restrictions



Notes: Annual data from RegData. Figure plots industries with the two largest and smallest changes in restrictions.

Figure 10: 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.

Figure 11: Aggregate Counterfactual, Entry and Monetary Policy

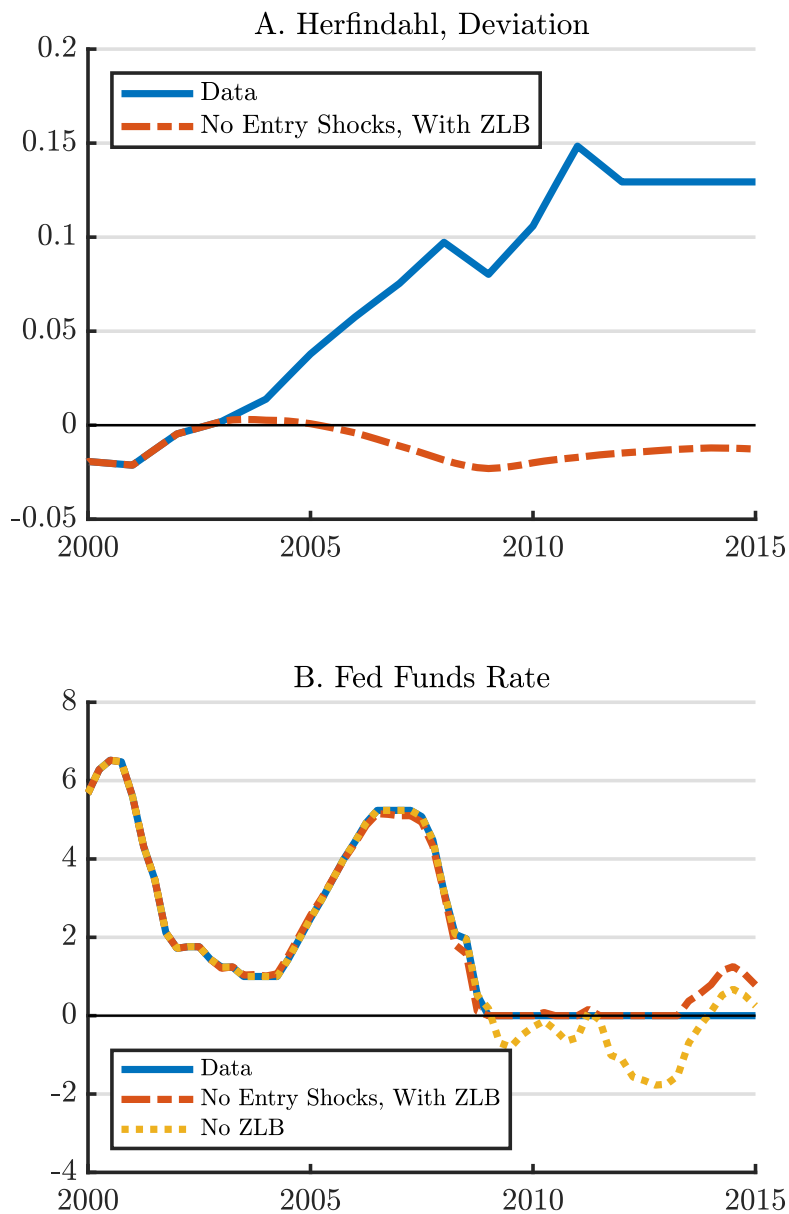


Figure 12: Log Capital and Consumption, Without ZLB and Without Entry Cost Shocks

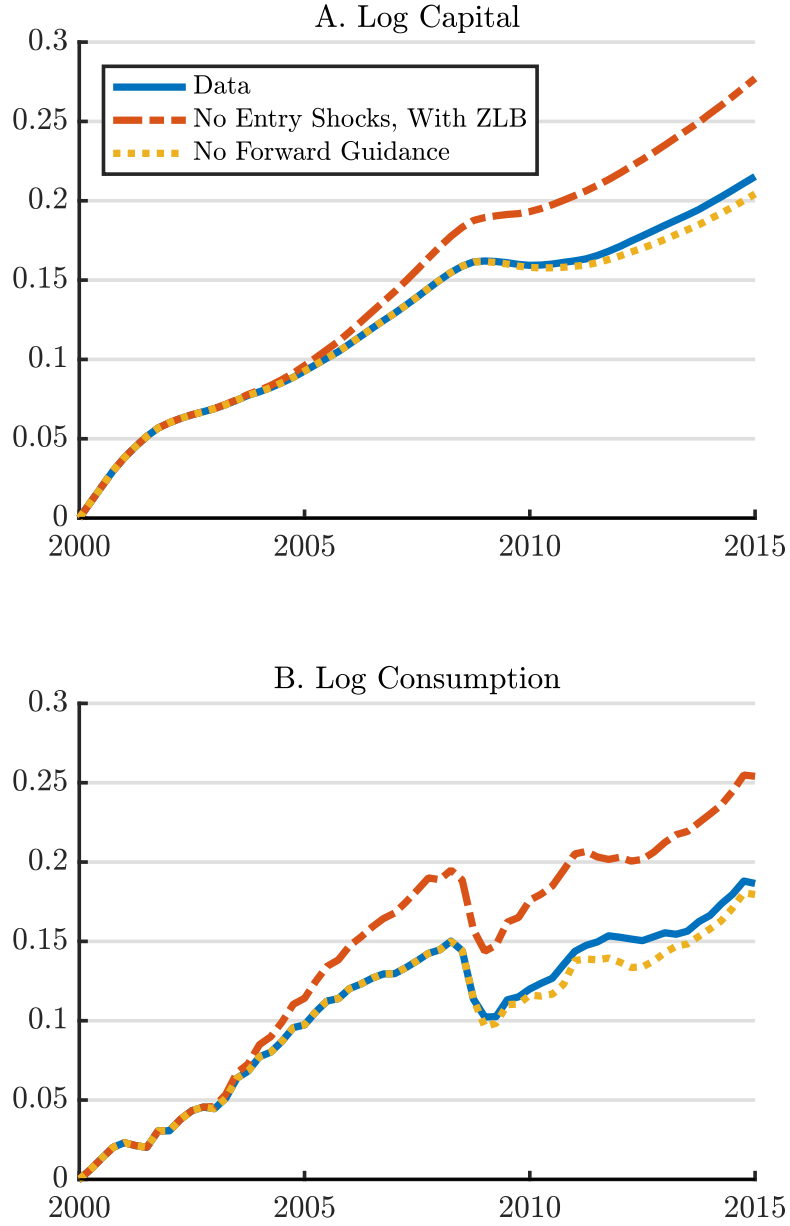
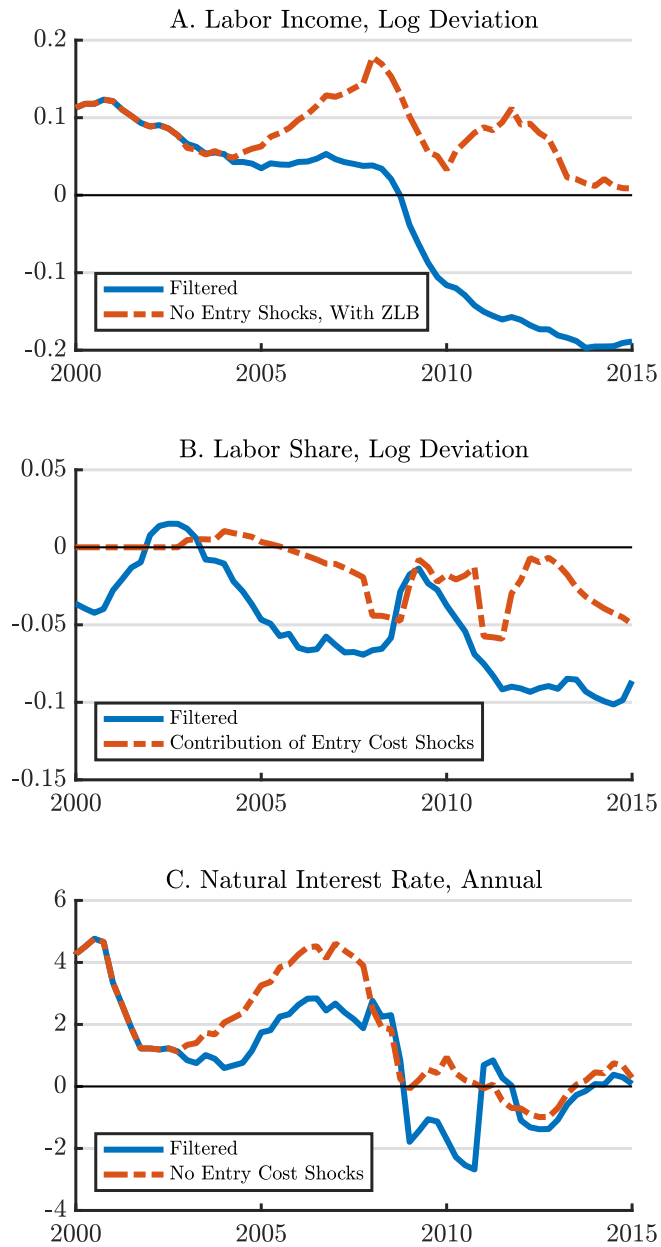


Figure 13: Labor Income, Labor Share, and Natural Interest Rate



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	$\bar{r}_t, \pi_t^p, c_t, x_t, \ell_t$	Aggregate
	Financial Accounts of the United States	$I, K, OS,$ and Q	Sector (NFCB, NFNCB)
Industry	BEA GDP by Industry	Output & prices	\sim NAICS L3
	BEA Fixed Assets Tables	I, K	\sim 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),²⁵ and non-farm business hours (FRED code PRS85006023 times the civilian employment level CE16OV, divided by the index CNP16OV). Consumption and inflation 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

²⁵We 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 Section 3 of the BEA Fixed Assets tables, available [here](#). Data includes current-cost and chained values for the net stock of capital, depreciation and investment. Note that BEA I and K include some intangible assets (i.e., software, R&D, and some intellectual property), in addition to 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. 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 segment.²⁶ Most industries map one-to-one. When this is not the case, we take the average number of restrictions across the given industries.

²⁶We 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	Dur_transp
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

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 cured = “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 GDP-byInd_GO_1947-2017.xls. Firms with NAICS codes 999 are dropped because they cannot be mapped to BEA industries.

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 to 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:²⁷

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

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

We aggregate concentration ratios using a nominal gross-output weighted average of industry-level concentration. Weighting by nominal output is appropriate in light of the model, but introduces some noise: the concentration ratio rises quickly in the late 2000’s and then falls (Figure A.4, left plot). This is because of large variation in the price of oil, and therefore the weight of the Nondurable Petroleum industry (right plot). Real output and the corresponding aggregate CR remain far more stable, which justifies holding the CR fixed after 2012 in our main counterfactual.

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 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

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

²⁷Because 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.

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, NBNIPPCCB, RCVSRNWBSNNB and RCVSNWBSNNB. Tobin's Q for the non-financial corporate sector is defined as

$$Q = \frac{V^e + (L - FA) - \text{Inventories}}{P_k K} \quad (27)$$

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. Bottom 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, regress $\frac{NI_{kt}}{K_{kt-1}}$ 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, simply compute the ratio of total M&A transaction

values to total Gross Output across BEA industries in our sample.

B Full Description of Model

Here, we provide an exposition of the elements of the model not described in the text.

B.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 $V_{j,t}^k$ denote the cum-dividend value (at the beginning of time t , before dividends are paid) of a capital-producing firm:

$$V_{j,t}^k = \mathbb{E}_t \sum_{i=0}^{\infty} \Lambda_{t+i} \text{Div}_{j,t+i}^k, \quad (28)$$

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

$$K_{j,t+1} = (1 - \delta) K_{j,t} + I_{j,t}. \quad (29)$$

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

$$\text{Div}_{j,t}^k = R_{j,t}^k K_{j,t} - I_{j,t} - \frac{\phi_k}{2} K_{j,t} \left(\frac{I_{j,t}}{K_{j,t}} - \delta \right)^2. \quad (30)$$

The firm's problem is to maximize (28) subject to (29) and (30). We can write the firm's objective as the dynamic programming problem

$$V_{j,t}^k(K_{j,t}) = \max_{I_{j,t}} \text{Div}_{j,t}^k + \mathbb{E}_t \left[\Lambda_{t+1} V_{j,t+1}^k(K_{j,t+1}) \right]. \quad (31)$$

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

$$\mathcal{V}_{j,t}^k = \max_{x_{j,t}} \left[R_{j,t}^k - x_{j,t} - \delta - \frac{\phi_k}{2} x_{j,t}^2 + (1 + x_{j,t}) \mathbb{E}_t \left[\Lambda_{t+1} \mathcal{V}_{j,t+1}^k \right] \right]. \quad (32)$$

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

$$x_{j,t} = \frac{1}{\phi_k} \left(Q_{j,t}^k - 1 \right), \quad (33)$$

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

$$Q_{j,t}^k \equiv \mathbb{E}_t \left[\Lambda_{t+1} \mathcal{V}_{j,t+1}^k \right] = \mathbb{E}_t \left[\Lambda_{t+1} \frac{V_{j,t+1}^k}{K_{j,t+1}} \right], \quad (34)$$

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

$$Q_{j,t}^k = \mathbb{E}_t \left[\Lambda_{t+1} \left(R_{j,t+1}^k + (1 + x_{j,t+1}) Q_{j,t+1}^k - x_{j,t+1} - \delta - \frac{\phi_k}{2} x_{j,t+1}^2 \right) \right], \quad (35)$$

which, given (33), can be written as

$$Q_{j,t}^k = \mathbb{E}_t \left[\Lambda_{t+1} \left(R_{j,t+1}^k + Q_{j,t+1}^k - \delta + \frac{1}{2\phi_k} \left(Q_{j,t+1}^k - 1 \right)^2 \right) \right]. \quad (36)$$

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.

B.2 Goods Producers

The goods-producing firms in industry j hire capital, labor, and an intermediate good 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. We describe the entry decision of firms in the main text, and here discuss the price-setting problem they face.

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

$$Y_{j,t} = D_{j,t} \left(\frac{P_{j,t}}{P_t} \right)^{-\sigma} Y_t. \quad (37)$$

The firms' output is aggregated into an industry output

$$Y_{j,t} = \left(\int_0^{N_{j,t}} y_{i,j,t}^{\frac{\epsilon_j-1}{\epsilon_j}} di \right)^{\frac{\epsilon_j}{\epsilon_j-1}}. \quad (38)$$

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:

$$P_{j,t} = \left(\int_0^{N_{j,t}} p_{i,j,t}^{1-\epsilon_j} di \right)^{\frac{1}{1-\epsilon_j}}. \quad (39)$$

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

$$\text{Div}_{i,j,t} = \max_{p_{i,j,t}, \ell_{i,j,t}, k_{i,j,t}, m_{i,j,t}} \frac{p_{i,j,t}}{P_t} y_{i,j,t} - \left(\frac{W_t}{P_t} \ell_{i,j,t} + m_{i,j,t} + R_{j,t}^k k_{i,j,t} + \phi \right), \quad (40)$$

subject to the production function

$$y_{i,j,t} = A_{j,t} k_{i,j,t}^\alpha h_{i,j,t}^{1-\alpha} \quad (41)$$

where $h_{i,j,t}$ is a CES aggregate of the intermediate input $m_{i,j,t}$, produced one-for-one from the final good, and labor $\ell_{i,j,t}$,

$$h_{i,j,t} = \left[(1-\psi)^{\frac{1}{\rho}} m_{i,j,t}^{\frac{\rho-1}{\rho}} + \psi^{\frac{1}{\rho}} \ell_{i,j,t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}.$$

The CES structure for $h_{i,j,t}$ yields the price index for $h_{i,j,t}$ as

$$P_{h,t} = \left[(1-\psi) P_t^{1-\rho} + \psi W_t^{1-\rho} \right]^{\frac{1}{1-\rho}},$$

and for a given $h_{i,j,t}$, we can write the allocation of the intermediate good and labor as

$$m_{i,j,t} = (1-\psi) \left[\frac{P_t}{P_{h,t}} \right]^{-\rho} h_{i,j,t}$$

$$\ell_{i,j,t} = \psi \left[\frac{W_t}{P_{h,t}} \right]^{-\rho} h_{i,j,t}.$$

The marginal cost depends on the price of the composition good (including real wages—there are no frictions in the labor market— and the price of intermediate goods) 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 $\chi_{j,t}$:

$$\chi_{j,t} = \frac{1}{A_{j,t}} \left(\frac{R_{j,t}^k}{\alpha} \right)^\alpha \left(\frac{P_{h,t}/P_t}{1-\alpha} \right)^{1-\alpha}. \quad (42)$$

Factor choices in the firm's problem imply the choice of capital and the composite good $h_{i,j,t}$ are simply $k_{i,j,t} = \alpha \frac{\chi_{j,t}}{R_{j,t}^k} y_{i,j,t}$ and $h_{i,j,t} = (1-\alpha) \frac{\chi_{j,t}}{P_{h,t}/P_t} y_{i,j,t}$. All goods-producing firms choose the same capital to composite goods ratio $\frac{k_{i,j,t}}{h_{i,j,t}} = \left(\frac{\alpha}{1-\alpha} \right) \frac{P_{h,t}/P_t}{R_{j,t}^k}$. Given they choose the same capital to intermediate goods ratio, all firms set the same price $p_{i,j,t} = P_{j,t}$ and choose the same level of output.

In the full model used for estimation we assume that firms face some nominal rigidities in order to obtain well-behaved industry Phillips curves.²⁸ 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 $\frac{p_{i,j,t}}{P_t} = \mu_j \chi_{j,t}$, where $\mu_j = \frac{\epsilon_j}{\epsilon_j - 1}$. The flexible industry-level price (39) becomes $\frac{P_{j,t}}{P_t} = \mu_j \chi_{j,t} N_{j,t}^{\frac{1}{1-\epsilon_j}}$. Since all firms have the same output, we can write

$$Y_{j,t} = \left(\int_0^{N_{j,t}} \frac{\epsilon_j - 1}{\epsilon_j} y_{i,j,t} di \right)^{\frac{\epsilon_j}{\epsilon_j - 1}} = y_{j,t} (N_{j,t})^{\frac{\epsilon_j}{\epsilon_j - 1}}. \quad (43)$$

where, with some abuse of notation, we denote by $y_{j,t}$ the average firm output in industry j . We see here the impact of product variety on productivity. The economy's flexible price index can be written as 1.

B.3 Households

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

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\gamma}}{1-\gamma} - \frac{\ell_t^{1+\varphi}}{1+\varphi} \right) \right], \quad (44)$$

subject to the budget constraint

$$S_t + P_t C_t \leq \tilde{R}_t S_{t-1} + W_t \ell_t, \quad (45)$$

²⁸Formally, 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 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

$$\Lambda_{t+j} = \beta^j \left(\frac{C_t}{C_{t+j}} \right)^\gamma. \quad (46)$$

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

$$\mathbb{E}_t \left[\Lambda_{t+1} \frac{P_t}{P_{t+1}} \tilde{R}_{t+1} \right] = 1. \quad (47)$$

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

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} (\beta \vartheta_w)^k \ell_{l,t+k} C_{t+k}^{-\gamma} \left(\frac{1 - \epsilon_w}{P_{t+k}} + \epsilon_w \frac{\text{MRS}_{t+k}}{W_t^*} \right) \right] = 0, \quad (48)$$

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

$$\text{MRS}_{l,t+k} \equiv \ell_{l,t+k}^\varphi C_{t+k}^\gamma. \quad (49)$$

B.4 Shocks

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

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

$$d_{j,t} = (1 - \tilde{\rho}_d) d_j + \tilde{\rho}_d d_{j,t-1} + \tilde{\sigma}_d \epsilon_{j,t}^d. \quad (50)$$

We estimate transitory shocks to $d_{j,t}$, or $\epsilon_{j,t}^d$, 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, as discussed in the text. 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.

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

$$\zeta_{j,t}^a = \tilde{\rho}_a \zeta_{j,t-1}^a + \tilde{\sigma}_a \epsilon_{j,t}^a \quad (51)$$

$$\zeta_t^a = \rho_a \zeta_{t-1}^a + \sigma_a \epsilon_t^a. \quad (52)$$

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 firms

$$q_{j,t}^k = \mathbb{E}_t \left[\lambda_{t+1} + \log \left(r_{j,t+1}^k + q_{j,t+1}^k + 1 - \delta + \frac{1}{2\phi_k} \left(q_{j,t+1}^k \right)^2 \right) \right] + \zeta_{j,t}^q + \zeta_t^q \quad (53)$$

$$q_{j,t}^\epsilon = \mathbb{E}_t [\lambda_{t+1} + v_{j,t+1}^\epsilon - k_{j,t+1}] + \zeta_{j,t}^q + \zeta_t^q, \quad (54)$$

where the industry-level shock $\zeta_{j,t}^q$ and the aggregate-level shock ζ_t^q are given by

$$\zeta_{j,t}^q = \tilde{\rho}_q \zeta_{j,t-1}^q + \tilde{\sigma}_q \epsilon_{j,t}^q \quad (55)$$

$$\zeta_t^q = \rho_q \zeta_{t-1}^q + \sigma_q \epsilon_t^q. \quad (56)$$

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

$$\kappa_{j,t} = \kappa + \zeta_{j,t}^\kappa + \zeta_t^\kappa, \quad (57)$$

where the industry and aggregate-level shocks are autoregressive processes

$$\zeta_{j,t}^\kappa = \tilde{\rho}_\kappa \zeta_{j,t-1}^\kappa + \tilde{\sigma}_\kappa \epsilon_{j,t}^\kappa \quad (58)$$

$$\zeta_t^\kappa = \rho_\kappa \zeta_{t-1}^\kappa + \sigma_\kappa \epsilon_t^\kappa. \quad (59)$$

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

$$\zeta_{j,t}^e = \tilde{\rho}_e \zeta_{j,t-1}^e + \tilde{\sigma}_e \epsilon_{j,t}^e \quad (60)$$

$$\zeta_t^e = \rho_\kappa \zeta_{t-1}^e + \sigma_e \epsilon_t^e. \quad (61)$$

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

$$\lambda_{t+1} = \log \beta - \gamma (c_{t+1} - c_t) + \zeta_t^b \quad (62)$$

$$\zeta_t^b = \rho_b \zeta_{t-1}^b + \sigma_b \epsilon_t^b. \quad (63)$$

- A shock to the monetary policy rule

$$\tilde{r}_t^* = -\log(\beta) + \phi_i \tilde{r}_{t-1}^* + (1 - \phi_i) (\phi_p \pi_t^p + \phi_y (\ln Y_t - \ln Y_t^F)) + \phi_g \ln \left(\frac{Y_t/Y_{t-1}}{Y_t^F/Y_{t-1}^F} \right) + \sigma_i \epsilon_t^i. \quad (64)$$

B.5 Equilibrium

The equilibrium of the model is given by:

1. Q investment equation

$$x_{j,t} = \frac{1}{\phi_k} [Q_{j,t}^k - 1]$$

2. Definition of $Q_{j,t}^k$

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

3. Definition of net investment $x_{j,t}$

$$x_{j,t} = \frac{K_{j,t+1}}{K_{j,t}} - 1$$

4. Goods-producers production function

$$y_{i,j,t} = A_{j,t} k_{i,j,t}^\alpha h_{i,j,t}^{1-\alpha}$$

5. Composite good input

$$h_{i,j,t} = \left[(1-\psi)^{\frac{1}{\rho}} m_{i,j,t}^{\frac{\rho-1}{\rho}} + \psi^{\frac{1}{\rho}} \ell_{i,j,t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}$$

6. Price of composite good

$$P_{h,t} = \left[(1-\psi)P_t^{1-\rho} + \psi W_t^{1-\rho} \right]^{\frac{1}{1-\rho}}$$

7. Allocation of intermediate good

$$m_{i,j,t} = (1-\psi) \left[\frac{P_t}{P_{h,t}} \right]^{-\rho} h_{i,j,t}$$

8. Allocation of labor

$$\ell_{i,j,t} = \psi \left[\frac{W_t}{P_{h,t}} \right]^{-\rho} h_{i,j,t}$$

9. Rental rate of capital

$$k_{i,j,t} = \alpha \frac{\chi_{j,t}}{R_{j,t}^k} y_{i,j,t}$$

10. Rental rate of intermediate good

$$h_{i,j,t} = (1-\alpha) \frac{\chi_{j,t}}{P_{h,t}/P_t} y_{i,j,t}$$

11. Definition of (real) dividends

$$\text{Div}_{i,j,t} = \frac{P_{j,t}}{P_t} y_{i,j,t} - \chi_{j,t} y_{i,j,t} - \phi$$

12. Goods-producers' value function

$$V_{j,t} = \text{Div}_{j,t} + (1-\delta_n) \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}$$

13. Evolution of the number of firms

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

14. Entry cost

$$p_{j,t}^e = (\kappa_{j,t} n_{j,t})^{\phi_n}$$

15. Free-entry

$$p_{j,t}^e \kappa_{j,t} \geq \mathbb{E}_t \Lambda_{t+1} V_{j,t+1}$$

16. Industry-level demand curve

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

17. Industry-level output

$$Y_{j,t} = y_{j,t} N_{j,t}^{\frac{\epsilon_j}{\epsilon_j - 1}}$$

18. Goods-market clearing

$$Y_t = C_t + K_{t+1} - (1 - \delta)K_t + \text{Capital Adjustment Costs}_t + N_{j,t}\phi + M_t$$

19. Pricing kernel

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

20. Euler equation

$$\Lambda_{t+1} = \beta \mathbb{E}_t \left[\frac{C_t}{C_{t+1}} \right]^\gamma$$

21. Marginal rate of substitution between labor and consumption

$$\text{MRS}_t = \ell_t^\varphi C_t^\gamma$$

22. Definition of the price level

$$P_t = \left[\int (P_{j,t})^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}}$$

23. Phillips curve on prices

$$\pi_{j,t}^p = \beta \mathbb{E}_t \pi_{j,t+1}^p + \lambda^p (\log \chi_{j,t} - \log \chi_j)$$

24. Phillips curve on wages

$$\pi_t^w = \beta \mathbb{E}_t \pi_{t+1}^w + \lambda^w \left(\log \text{MRS}_t - \log \frac{W_t}{P_t} \right)$$

25. Real wage

$$\log \frac{W_t}{P_t} = \log \frac{W_{t-1}}{P_{t-1}} + \pi_t^w - \pi_t^p$$

26. Taylor Rule

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

27. Aggregation of capital used by firms: $K_t = \int N_{j,t} k_{i,j,t} dj$, where $k_{i,j,t}$ is the average capital used by firms.

28. Aggregation of intermediate goods used: $M_t = \int N_{j,t} m_{i,j,t} dj$.

29. Aggregation of labor supply: $\ell_t = \int N_{j,t} \ell_{i,j,t} dj$.

The variables are: $x_{j,t}$, $Q_{j,t}^k$, $P_{j,t}$, Λ_t , $R_{j,t}^k$, $K_{j,t}$, $y_{j,t}$, $k_{j,t}$, $h_{i,j,t}$, $m_{i,j,t}$, $\ell_{i,j,t}$, $P_{h,t}$, P_t , W_t , $\chi_{j,t}$, $\text{Div}_{j,t}$, $V_{j,t}$, $N_{j,t}$, $n_{j,t}$, $p_{j,t}^e$, $Y_{j,t}$, Y_t , C_t , M_t , \tilde{R}_t , ℓ_t , K_t , $\pi_{j,t}^p$, π_t^w . We compute the flexible price level of output Y_t^F from a set of equations corresponding to the ones above, but with no pricing frictions.

C Additional Results and Figures

In this section, we present additional results and figures.

C.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.

Table A.3: Robustness of Estimated Parameters

Parameter	(1)			(2)		
	Median	10%	90%	Median	10%	90%
σ	0.4	0.4	0.4	0.4	0.4	0.4
ϕ_n	1.7	1.2	2.3	2.1	1.6	2.9

(1): Same $\epsilon_j = 5$ for all industries.

(2): Q_t observed matched to total industry Q .

C.2 Additional Figures

- Figure A.1 plots impulse response functions for five shocks in our aggregate model. The aggregate entry cost shock is key for describing the evolution of the number of firms at the aggregate level, and generates comovement in aggregate consumption, investment, and inflation.
- Figure A.2 plots our filtered aggregate entry cost shock series against aggregate measures of regulation and an aggregate measure of M&A activity. The correlation with the measure of regulation is .26 while the correlation for M&A/GO is .45.
- Figure A.3 plots the distribution of estimated beliefs about steady-state demand across industries. Most beliefs are centered around their true value of $\log D_{j,t} = 0$, with some industries with notably higher beliefs about demand, including the information and computing industries.
- Figure A.4 shows that weighting by nominal output introduces noise in the evolution of aggregate concentration (left plot). This is because of large variation in the price of oil, and therefore the weight of the Nondurable Petroleum industry (right plot). Real output and the corresponding aggregate CR remain far more stable, which justifies holding the CR fixed after 2012 in our main counterfactual.

- Figure A.5 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.6 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.5). This ratio is roughly constant over time for most industries.
- Figure A.7 plots the Gelman-Rubin diagnostic for the convergence of the posterior distributions along the two chains in the baseline industry estimation. The diagnostic across parameters is below the 1.2 level commonly used to indicate convergence (see Brooks, S. and A. Gelman, (1998), 'Monitoring Convergence of Iterative Simulations', Journal of Computational and Graphical Statistics, Volume 7, Number 4, Pages 434–455).
- Figure A.8 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.9 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.
- Figure A.10 validates that our model's implied path of the entry rate of firms lines up with the entry rate from Census data, with a correlation of 0.54 between the two series, capturing the decline in entry rates documented by a number of papers discussed in the Introduction.

C.2.1 Aggregate Data

Figure A.11 plots the aggregate data used in estimation of the aggregate model. We describe how these series are constructed above.

C.2.2 Industry Data in Estimation

Figures A.12 through A.16 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: Aggregate Impulse Response Functions

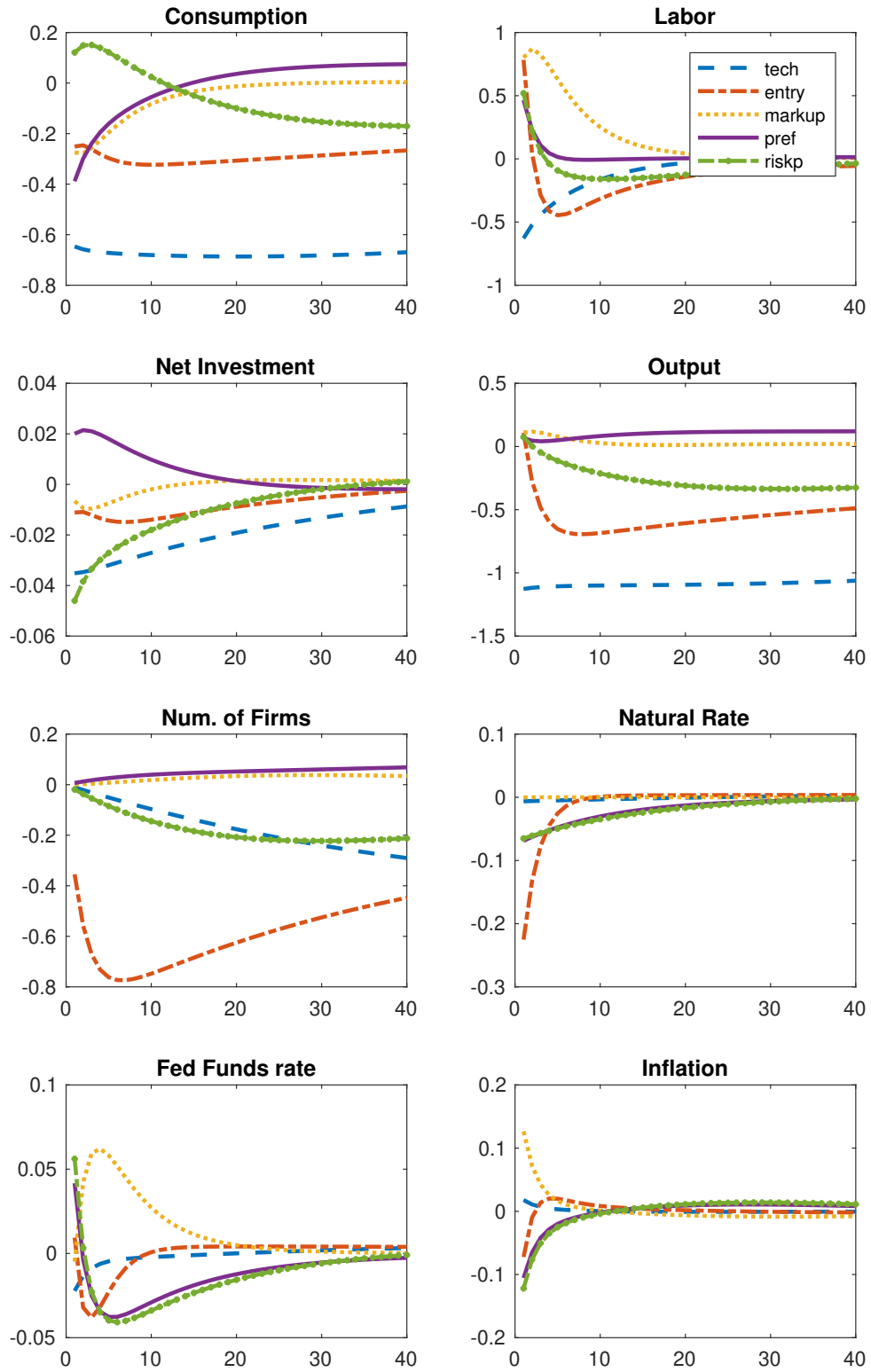
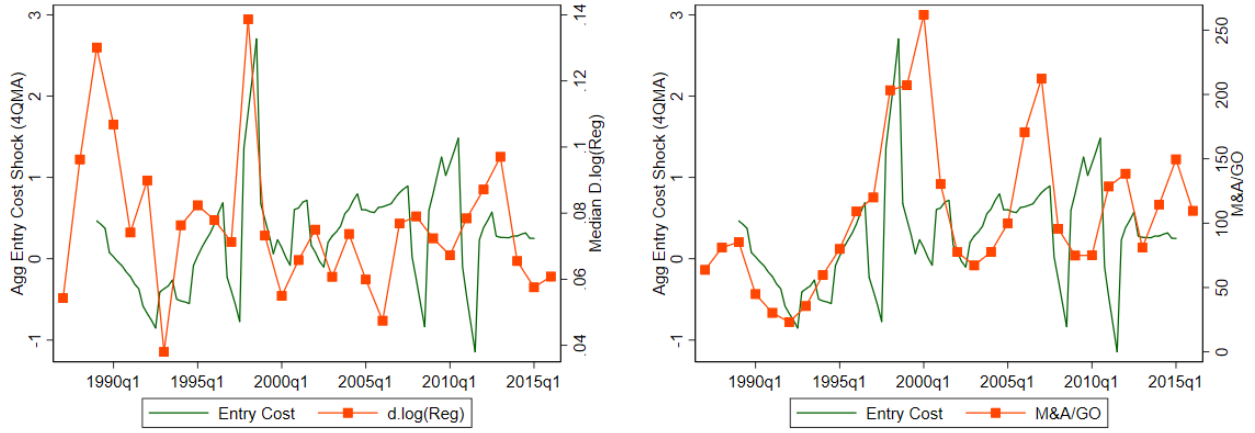


Figure A.2: Aggregate Entry Cost Shocks vs. Regulation and M&A



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

Figure A.3: Mode of Estimated Posterior Distributions of Expected Demand Across Industries

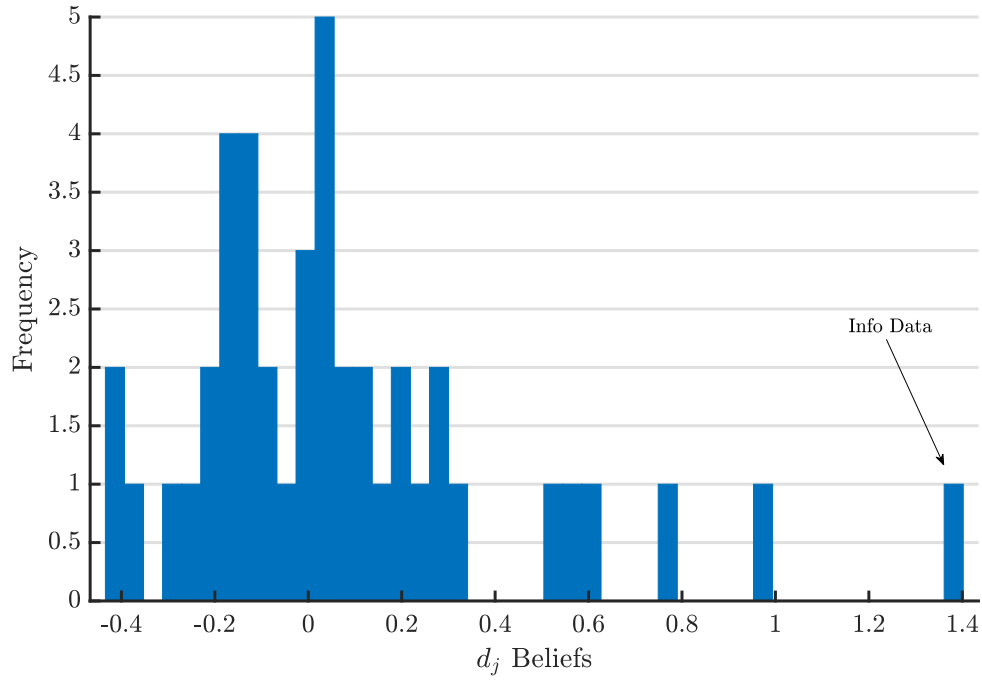


Figure A.4: Aggregated Concentration Series

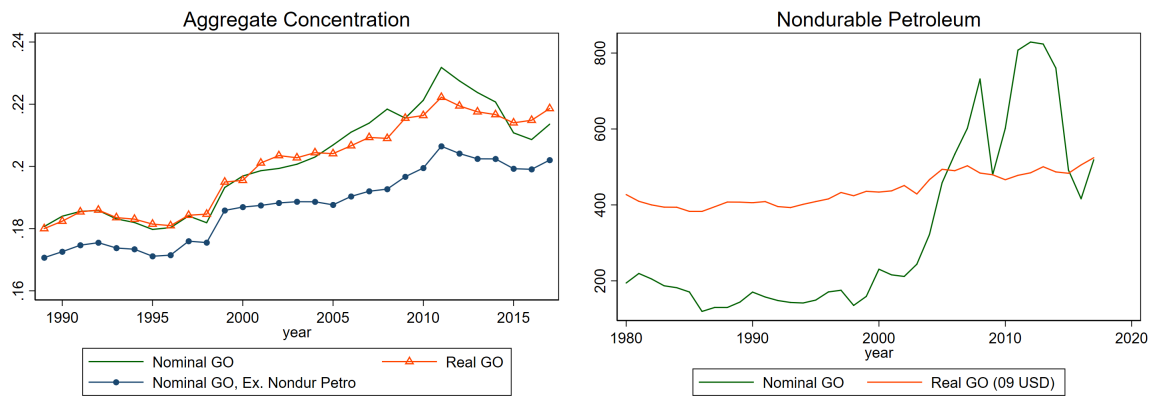


Figure A.5: Distribution of Calibrated Firm-Level Elasticity of Substitution

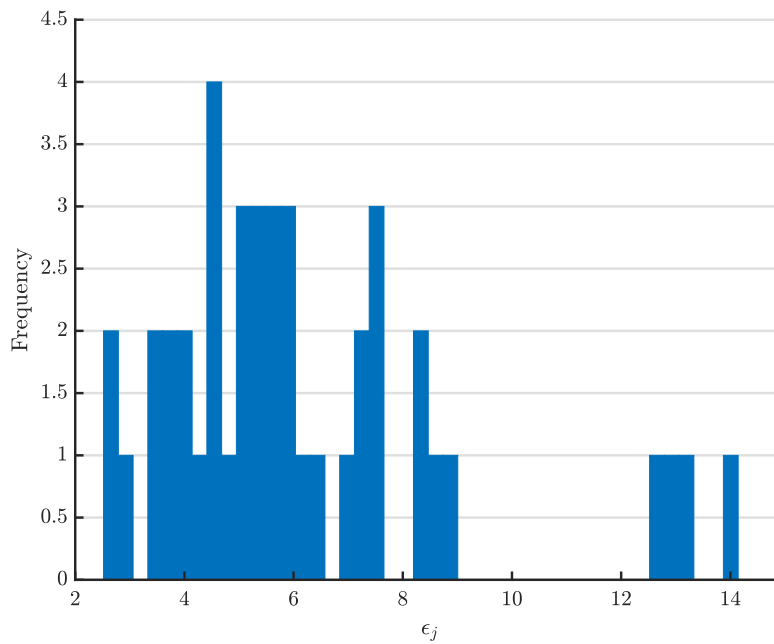


Figure A.6: Industry Gross Operating Surplus to Output Ratio

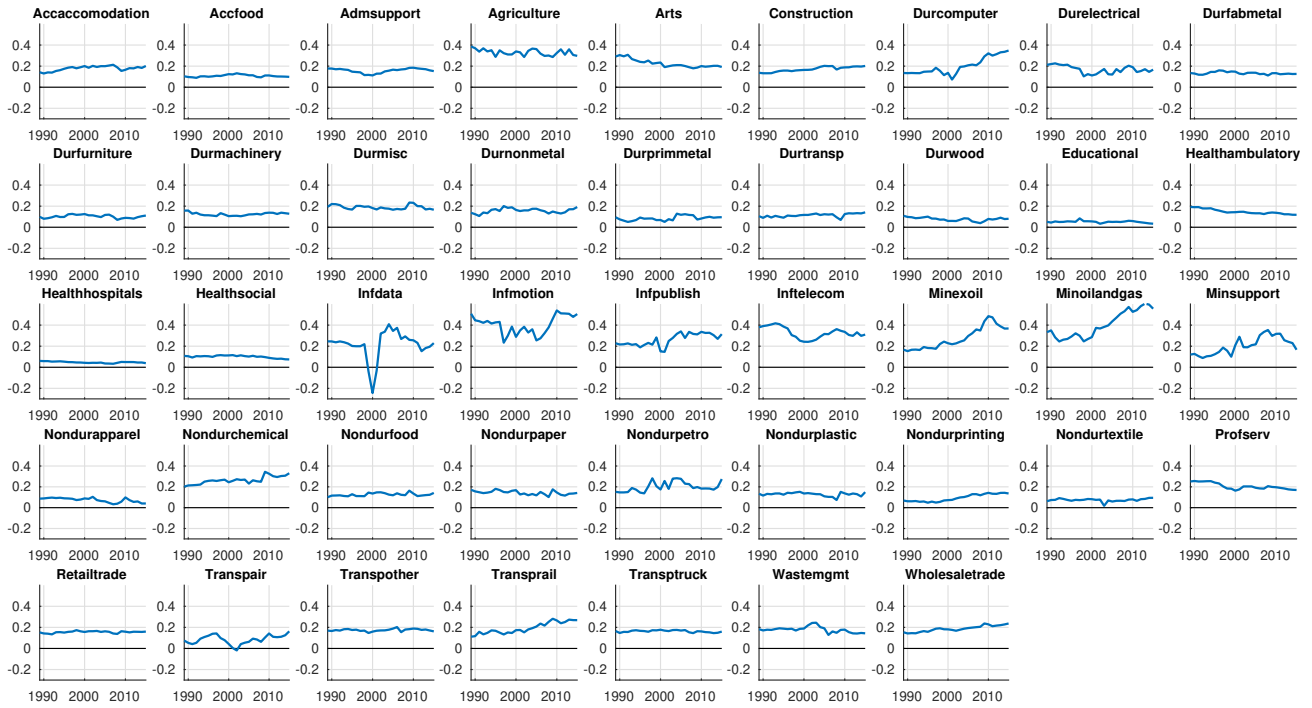


Figure A.7: Convergence of Posterior Distributions in Estimated Industry Model

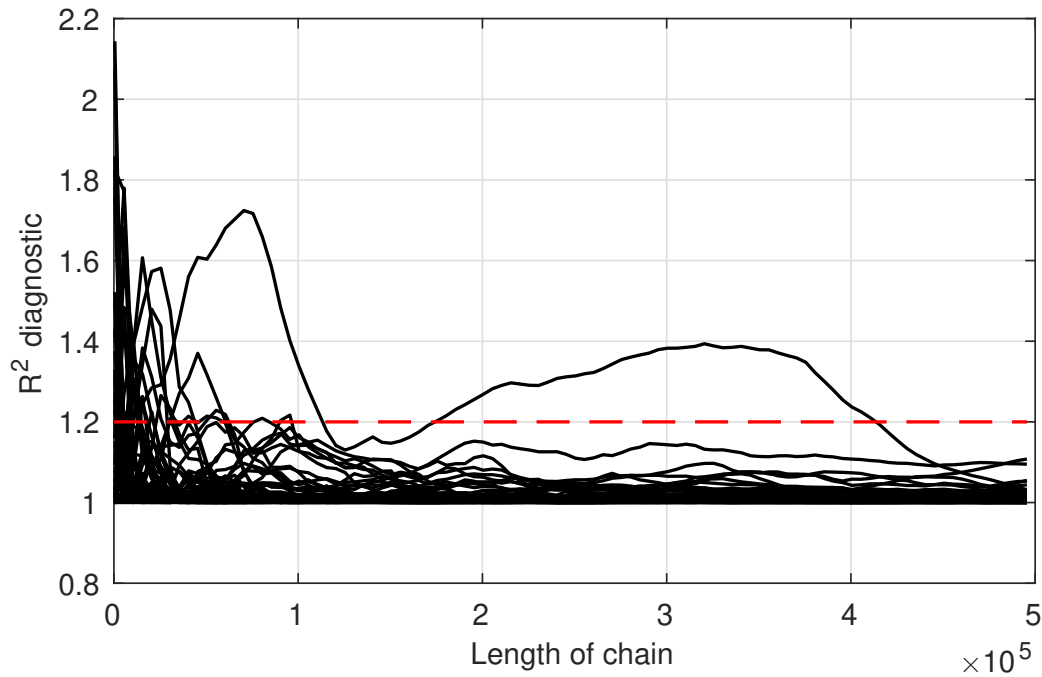
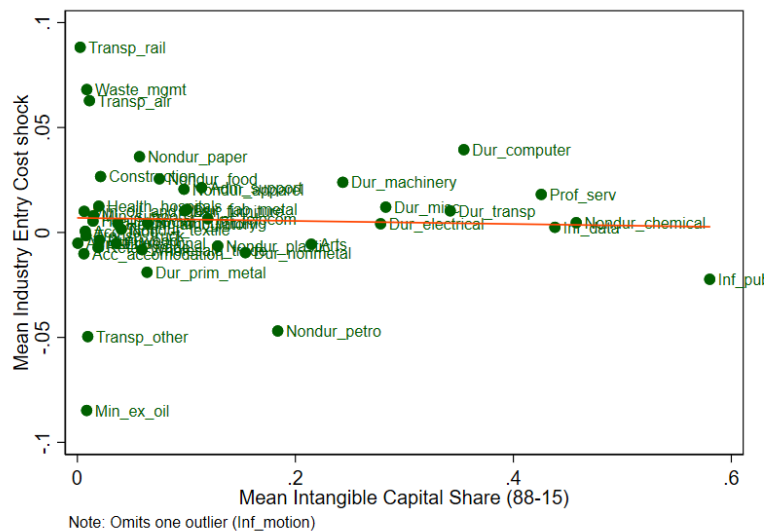


Figure A.8: Industry Entry Cost Shocks vs. Intangible Intensity



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

Figure A.9: Aggregate Entry Cost Shocks at the Zero Lower Bound

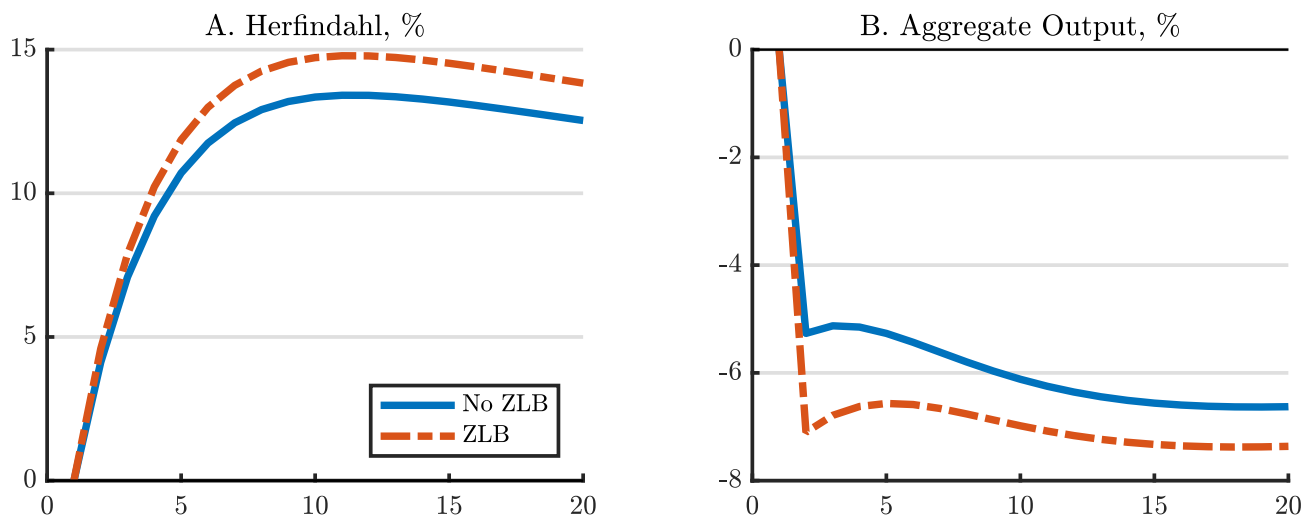


Figure A.10: Entry in Model Versus the Data

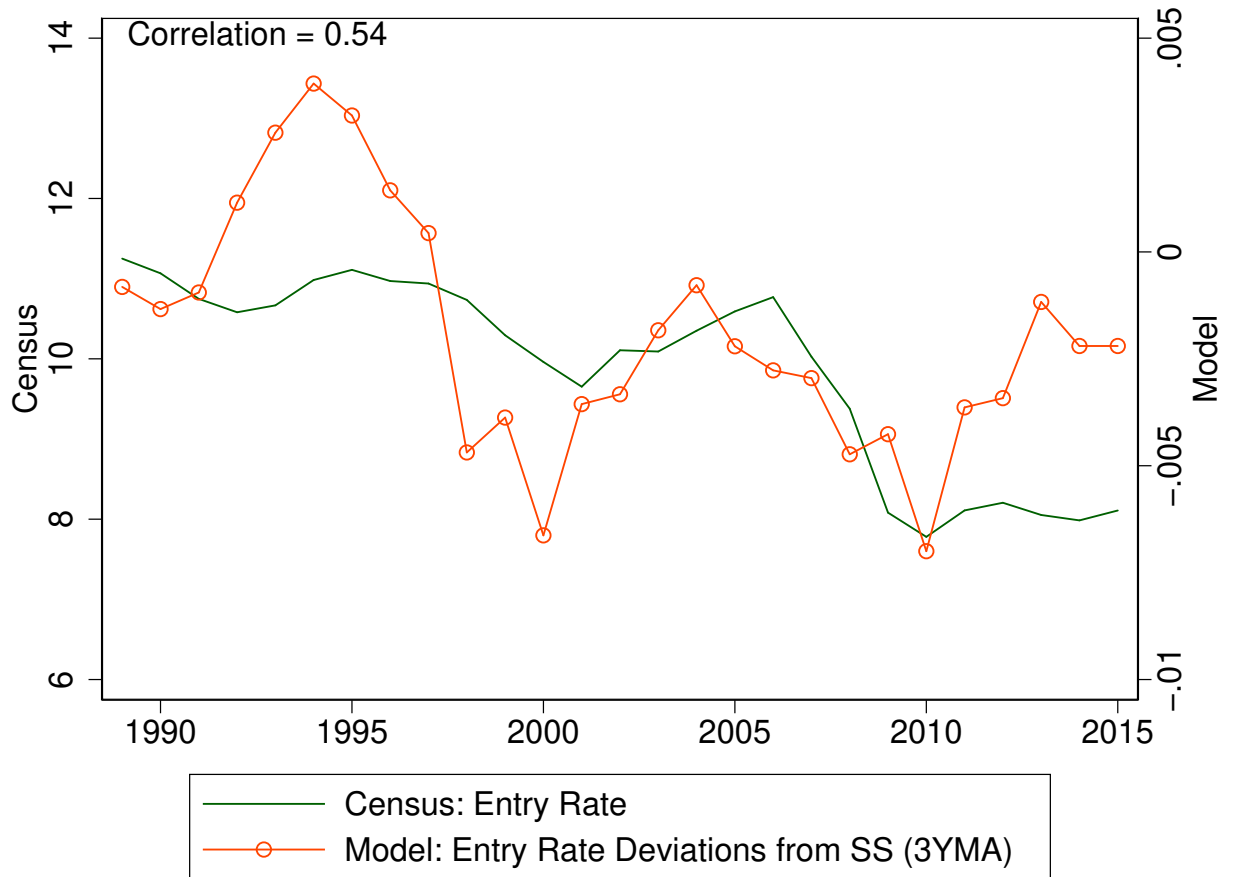


Figure A.11: Aggregate Data in Estimation

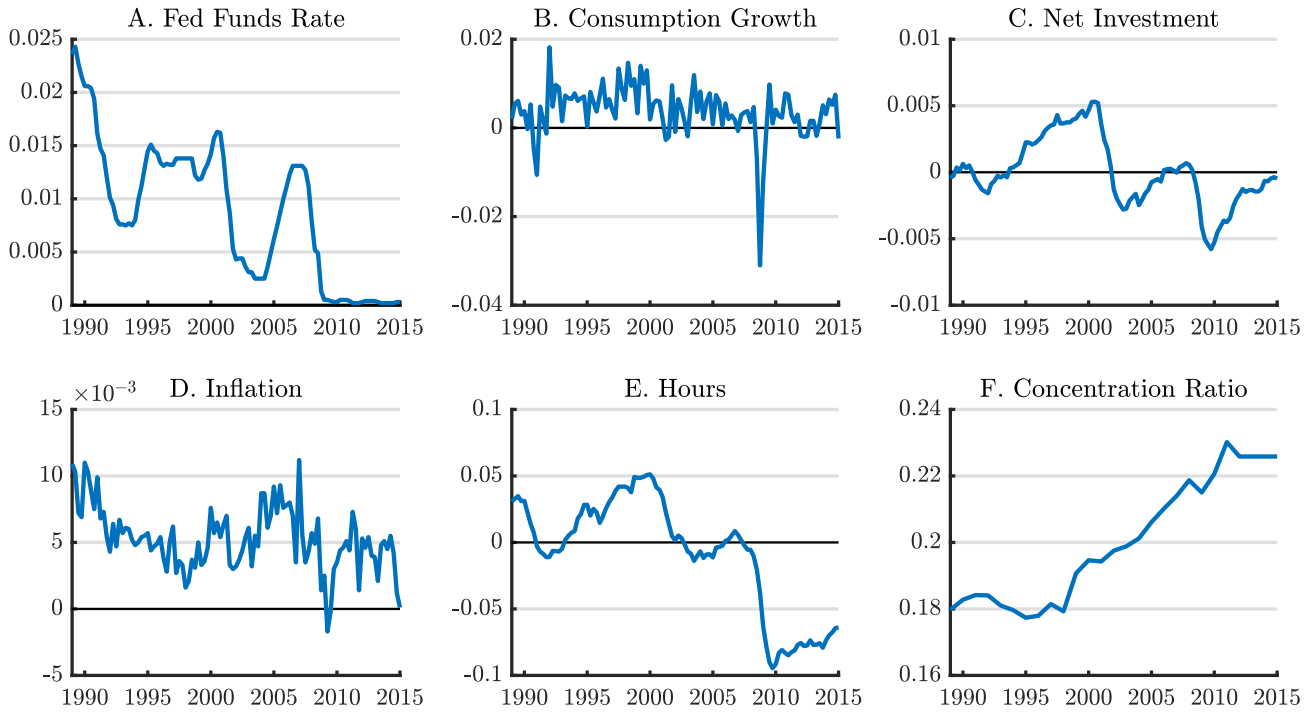


Figure A.12: Industry Data in Estimation, Nominal Output

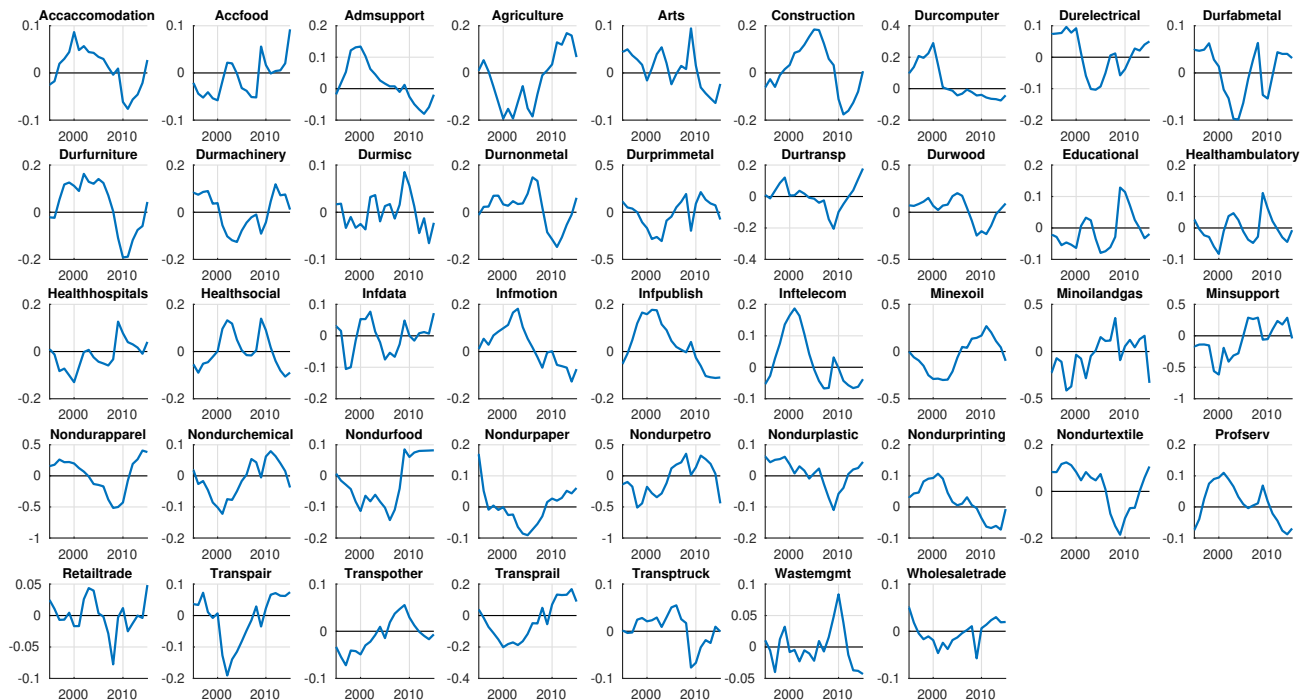


Figure A.13: Industry Data in Estimation, Capital

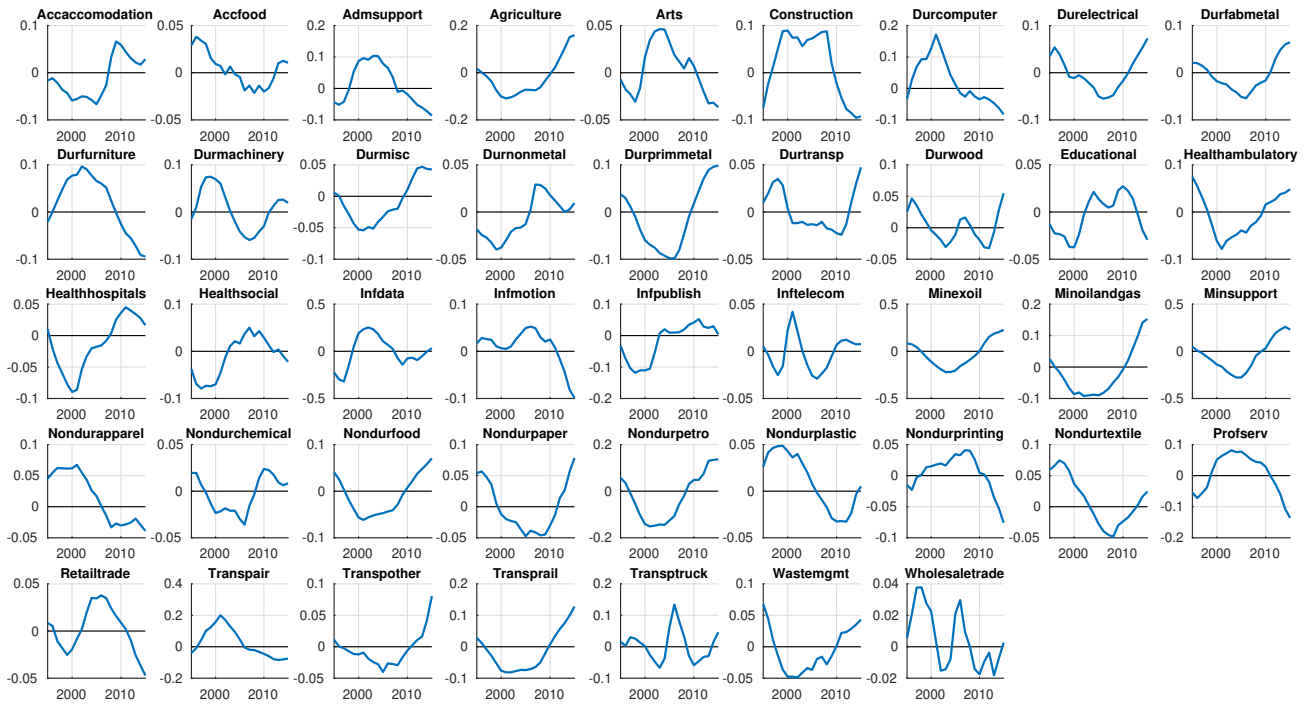


Figure A.14: Industry Data in Estimation, Concentration Ratio

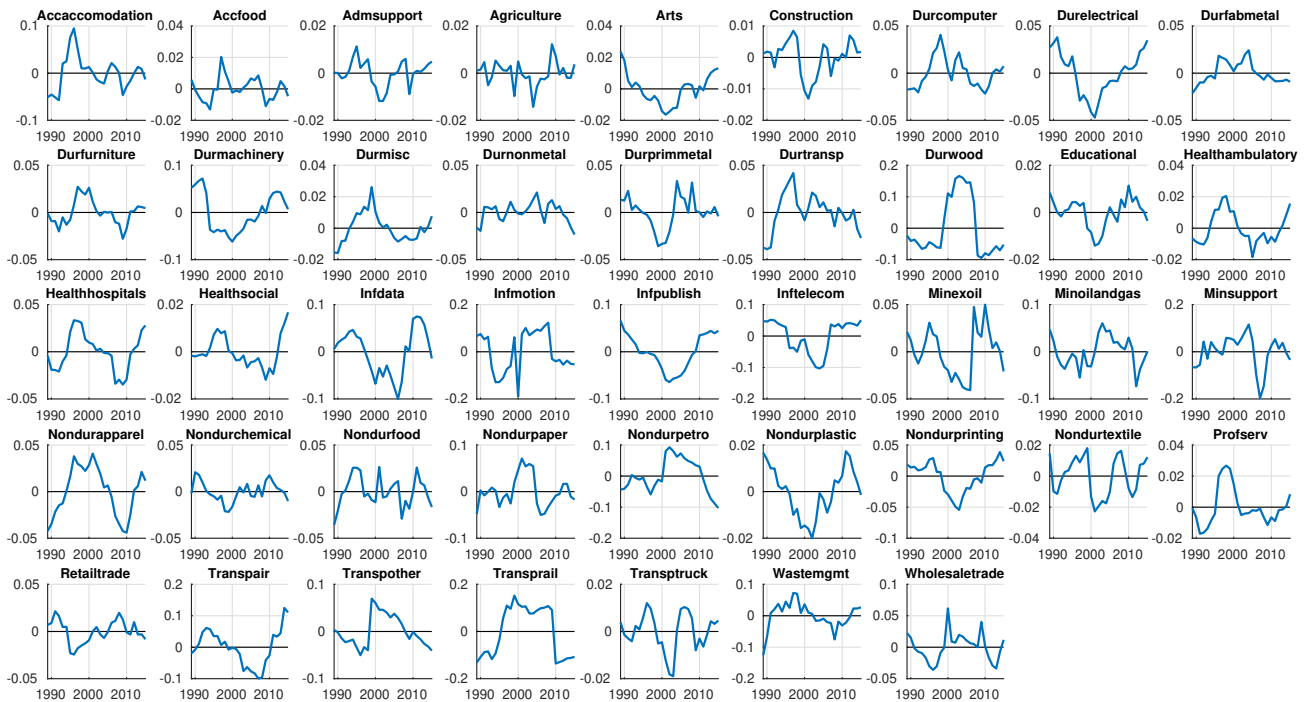


Figure A.15: Industry Data in Estimation, Q

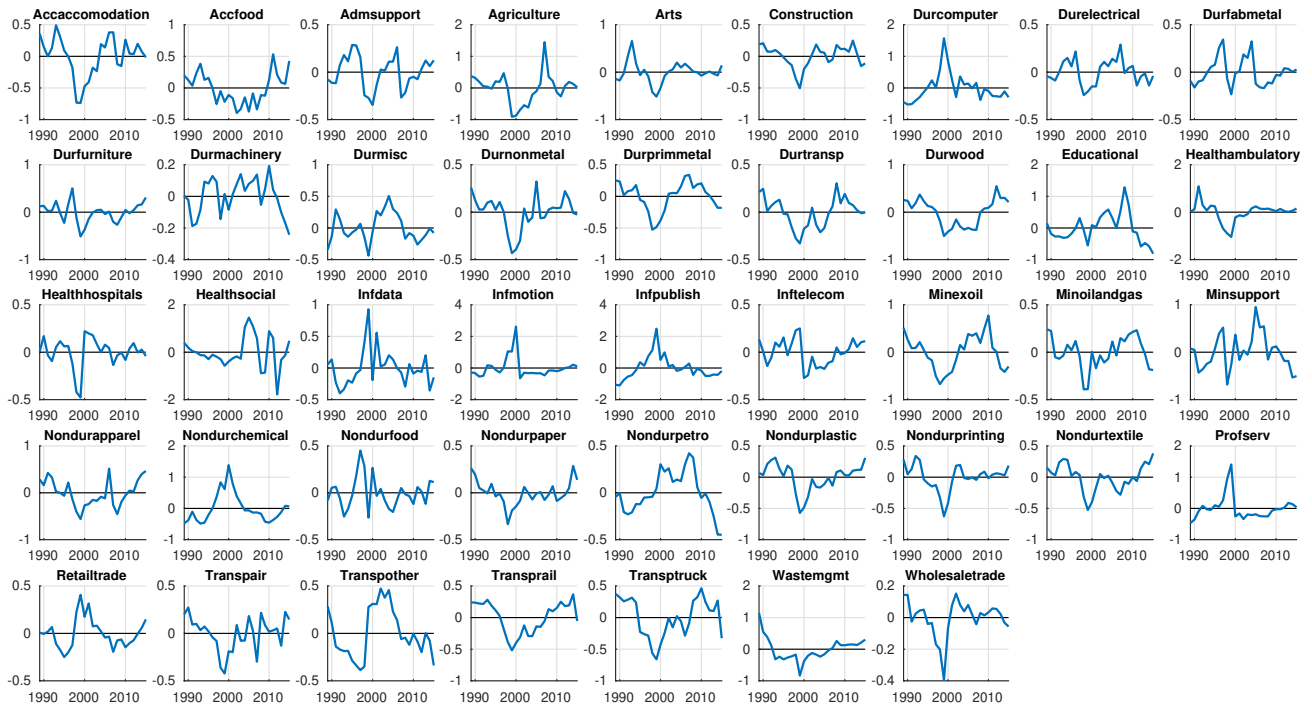


Figure A.16: Industry Data in Estimation, Price Inflation

