Market Power and Macroeconomic Fluctuations *

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Abstract

Crises affect firms unequally. For example, natural disasters disrupt only those firms that are located in specific regions. Financial crises particularly impact those firms that require external financing. This paper studies the aggregate effects of shocks that affect a subset of firms in many industries—referred to as *asymmetric supply shocks*. Based on a heterogeneous-firm model with oligopolistic competition, calibrated to firm-level data, I show two main results. First, asymmetric supply shocks can account for a quarter of fluctuations in aggregate output. Second, a higher intensity of competition among firms makes aggregate output higher on average, but also more volatile over time. The reason is that intense competition, by curtailing firms' market power, fosters the reallocation of inputs from less productive to more productive firms in the face of asymmetric supply shocks.

Keywords: market power, oligopoly, firm heterogeneity, asymmetric supply shocks, aggregate fluctuations, competition policy
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1 Introduction

Crises affect firms unequally. Typically, their direct effects concentrate on some subset of firms, as the following examples illustrate. Natural disasters, such as floods or earthquakes, disrupt the production only of those firms that are located in a specific region. Financial crises directly impact only those firms that require external financing to fund their operations. Both of these supply disruptions are neither aggregate, nor industry-specific, nor firm-specific. Instead, they affect some firms more than others within many industries. I collectively refer to such disruptions as *asymmetric supply shocks*.

This paper studies the aggregate effects of asymmetric supply shocks. To this end, I build a heterogeneous-firm model with oligopolistic competition. I show that even though asymmetric supply shocks may directly affect only a subset of firms, they trigger a *strategic response* from *all* firms. For example, if a negative shock disrupts the production of some firms, all competing firms face a higher demand for their goods, to which they typically respond by producing more and also selling at a higher price. To document asymmetric supply shocks empirically and ultimately calibrate the model, I draw on firm-level data. The vast majority of fluctuations in firm-level sales cannot be explained by aggregate or industry-specific shocks. Yet, the residual fluctuations do not simply reflect firm-specific shocks, as few common components can explain a substantial share of them. The presence of these common components suggests that there are asymmetric supply shocks that cause fluctuations in firm-level sales. According to the calibrated model, asymmetric supply shocks can account for around 25% of fluctuations in aggregate output and 70% of fluctuations in the labor share. Finally, I show that the intensity of competition among firms matters. In the face of asymmetric supply shocks, more intense competition implies that firm-level markups change less and firm-level labor changes more such that there is a better reallocation of inputs from low- to high-productivity firms. Therefore, the economy as a whole makes better use of positive shocks while being more resilient to negative shocks. In sum, more intensive competition implies that aggregate output is higher on average, but potentially also more volatile. The optimal intensity of competition needs to trade off these effects.

In more detail, to investigate the aggregate effects of asymmetric supply shocks, I study a model environment with two key features—firm heterogeneity and imperfect competition. I build on the oligopoly framework of Atkeson and Burstein (2008) to introduce imperfect competition. There is a large number of industries and, in each of them, a small number of firms that produce differentiated goods. Due to the limited number of firms in each industry, firms have market power and interact strategically. Competing firms are heterogeneous in their productivity levels and the distribution of productivity fluctuates over time and differs across industries, similar to Burstein et al. (2020). Asymmetric supply shocks affect one or more firms differently than one or more other firms within many industries. Thereby, they change the distribution of productivity—and hence of output, sales, and markups—across firms in many industries with consequences for economy-wide aggregates. Microfoundations for asymmetric supply shocks include regional shocks when competitors from many industries are located in different regions and financial shocks when there are financially constrained and unconstrained firms in many industries.[1]

As a first step, I use the model to qualitatively study the transmission of asymmetric supply shocks and to distinguish three effects. First, there is a direct effect to the productivity of a subset of firms in each industry. In the absence of further effects, the aggregate implications would be straightforward—a 10% shock to 50% of firms reduces aggregate productivity by 5%. However, second, the direct effect to some firms triggers a strategic response from all firms, resulting from their profit-maximizing behavior. Firms hit by a negative shock reduce their labor input and hence production beyond the direct effect, while also reducing their markup over marginal costs. In contrast, firms not directly affected by the negative shock face a higher demand for their goods and increase labor input and production, but also markups. These strategic responses have two implications. On the one hand, labor is reallocated away from firms that experienced a drop in productivity, such that aggregate productivity falls less than in the absence of reallocation. On the other hand, the aggregate markup changes due to within-firm markup changes and the reallocation of production to firms with higher productivity and hence also a higher markup. These strategic responses are the most interesting effects since they are relevant for the transmission of asymmetric supply shocks and firm-level shocks, but not for aggregate or industry-specific shocks. Third, there is a general equilibrium effect as the representative household reacts to the changes in aggregate productivity and the aggregate markup.

In the second step, I document the existence of asymmetric supply shocks in firm-level data from the U.S. Compustat database. By applying time and industry-by-time fixed effects, I show that the vast majority of fluctuations in firm-level sales are not driven by aggregate or industry-specific shocks. The residual volatility could reflect firm-specific shocks or asymmetric supply shocks. The crucial difference between the two is that asymmetric supply shocks induce a correlation of firm-level sales residuals across industries, while firm-specific shocks do not. Using principal component analysis, I document that the first

[1] An example of regional shocks would be Atkeson and Burstein (2008) who study a two-country model with country-specific productivity shocks. Financial shocks with financially constrained and unconstrained firms are studied in Khan and Thomas (2013) and Khan et al. (2016). When borrowing constraints are endogenous, monetary policy shocks as in Ottonello and Winberry (2020) or fiscal policy shocks as in Koby and Wolf (2020) also have an asymmetric component.

common component (the first three common components) can explain almost 22% (40%) of the volatility in firm-level sales residuals, suggesting the presence of quantitatively relevant asymmetric supply shocks.

Next, I use the evidence from the empirical analysis using firm-level data, alongside aggregate data, to calibrate the model to the U.S. economy. Based on model simulations, I show that asymmetric supply shocks can account for 28% of fluctuations in aggregate output, 27% of fluctuations in labor, and 68% of fluctuations in the labor share. This showcases that asymmetric supply shocks are a quantitatively relevant driver of business cycle fluctuations.

In addition, I use the calibrated model to investigate how a higher intensity of competition changes the strategic responses of firms to asymmetric supply shocks and thereby their aggregate effects. It is well-known that a higher intensity of competition, modeled with a higher number of firms per industry, reduces firm-level markups and thereby leads to higher steady-state output and higher welfare (Edmond et al., 2018). I show that in addition to this effect, the fluctuations around the steady state caused by asymmetric supply shocks are also affected by a higher intensity of competition. When a negative shock disrupts the production of some firms, their unscathed competitors face a higher demand for their goods and typically respond by raising production as well as markups. It is profit-maximizing for them to increase markups because their market power has risen, i.e. their elasticity of demand has fallen. A higher intensity of competition implies that the market power of unaffected firms increases less, such that they increase markups less and instead increase labor input and thereby production more. This implies that there is more reallocation of inputs from low-productivity to high-productivity firms, which dampens the drop in aggregate productivity and therefore in aggregate output. Vice versa, in the face of a positive shock to some firms, more reallocation means that the rise in aggregate productivity is larger. In sum, a higher intensity of competition implies that aggregate productivity becomes more strongly non-linear—falling less with negative shocks and rising more with positive shocks. Due to this non-linearity, average output (over time) generally exceeds steady-state output and more so when the intensity of competition is high. However, the same non-linearity implies that output potentially also becomes more volatile. A higher intensity of competition also implies that in the face of asymmetric supply shocks, the average markup, which generally exceeds the steady-state markup, is lower on average and potentially less volatile. This is the case if the dampening of within-firm markup changes dominates the reallocation to high-markup firms. Quantitatively, I show that increasing the number of firms per industry from 5 (baseline calibration) to 20 increases steady-state output by around 3% and average output (relative to steady-state output) by another 3%. At the same time, the volatility of output increases by 78%. The higher volatility reflects that the higher volatility of productivity dominates the lower volatility of the aggregate markup. In sum, the optimal intensity of competition needs to trade off a better average state of the economy with a higher volatility of output.

Related Literature. This paper seeks to combine insights from the literatures studying the aggregate implications of firm heterogeneity and of imperfect competition among firms, respectively. Many contributions to the former literature show that firm-level frictions, including financial frictions (Khan and Thomas, 2013; Khan et al., 2016; Ottonello and Winberry, 2020) and real frictions (Koby and Wolf, 2020; Gnewuch and Zhang, 2024), make firms differentially exposed to macroeconomic shocks, providing microfoundations for *asymmetric supply shocks*. However, these contributions abstract from imperfect competition among firms, such that firms react to the direct effects of shocks as well as to general equilibrium effects, but do not react strategically to asymmetric effects between them and their competitors. These strategic interactions are prevalent in the latter literature on imperfect competition among firms (Burstein et al., 2020). However, this literature focuses on firm-specific shocks and does not study asymmetric supply shocks. In sum, this paper studies the aggregate effects of asymmetric supply shocks—as common in the literature on firm heterogeneity—in a framework in which firms interact strategically—as common in the literature on imperfect competition.

In more detail, this paper relates to a growing literature on the implications of imperfect competition among firms and endogenous market structure for macroeconomic outcomes. One strand of this literature has focused on long-run trends. De Loecker et al. (2020) and Covarrubias et al. (2020) document substantial increases in markups, industry concentration, and profit rates in the United States over the past decades and discuss their macroeconomic implications. Kim and Savagar (2023) document declining firm-level revenue elasticities. Another strand of this literature has focused on the interaction of aggregate shocks with the market structure. Jaimovich and Floetotto (2008) and Bilbiie et al. (2012) show how firm entry and exit amplifies the aggregate effects of productivity shocks in frameworks with endogenous markups. Mongey (2021) finds a larger degree of monetary non-neutrality under oligopolistic competition than under monopolistic competition in a dynamic setting with price rigidities. Burstein et al. (2020) extend the granular macroeconomic model of Gabaix (2011) to oligopolistic competition and show that variable markups dampen the aggregate effects of idiosyncratic shocks. Furthermore, the intersection of these two strands, i.e. the implications of the current market structure and intensity of competition for the amplification of aggregate shocks, has been investigated. Wang and Werning (2022) find that higher industry concentration leads to a larger degree of monetary non-neutrality in a framework with price rigidities. Ferrari and Queirós (2022) show that the amplification of aggregate productivity shocks via firm entry and exit is stronger when idiosyncratic productivity is more dispersed because more firms are close to the entry (exit) threshold. Jaimovich and Floetotto (2008) and Corhay et al. (2020) also study aggregate productivity shocks and their amplification via endogenous entry and exit. They find that higher markups are associated with a higher aggregate volatility, because of the convex relationship between markups and the number of homogeneous firms. Finally, Bilbiie et al. (2019), Edmond et al. (2018), and Boar and Midrigan (2019) discuss the welfare costs of markups and optimal competition policy in macroeconomic models. I add to this literature by introducing asymmetric supply shocks, studying their aggregate effects, and the relevance of the intensity of competition among firms.

Any shock that changes the distribution of sales among firms in an industry is also asymmetric and can thus be considered an asymmetric supply shock. Therefore, this paper relates to a large body of work investigating the transmission of aggregate shocks in models with some form of firm heterogeneity. For example, the presence of financial frictions in the models of Khan and Thomas (2013), Khan et al. (2016), and Ottonello and Winberry (2020) implies that any aggregate shock propagates asymmetrically. As a result, the mechanism highlighted in this paper becomes relevant as soon as the assumption of a continuum of firms which do not interact strategically—a common simplification in models with firm heterogeneity—is dropped.

Finally, the shocks that I introduce—asymmetric supply shocks—relate to the literature on the supply-side origins of aggregate fluctuations. Early contributions have proposed aggregate (e.g. Kydland and Prescott 1982) and sector-specific (e.g. Long and Plosser 1983) supply shocks, typically to productivity, as drivers of business cycles. More recently, firm-specific shocks have been proposed as a source of aggregate fluctuations (e.g. Gabaix 2011, Carvalho and Grassi 2019). Motivated by the COVID-19 crisis, Guerrieri et al. (2022) study shocks to a subset of sectors of the economy. I add to this literature by introducing and studying *shocks to a subset of firms within many industries*, referred to as asymmetric supply shocks. In contrast to aggregate shocks, sector-specific shocks, and shocks to a subset of sectors, asymmetric supply shocks affect the market structure within industries (sectors[2]), because they do not affect all firms in an industry symmetrically. In contrast to firm-specific shocks, asymmetric supply shocks affect firms in many industries and do not vanish by a

[2] The terms “sector” and “industry” both describe a group of firms that operate in the same segment of the economy. A “sector” typically describes a large segment of the economy, e.g. the manufacturing sector, while an “industry” typically refers to a smaller, more specific group of firms. Since I am interested in the strategic interaction of small groups of firms, I discuss “industries” throughout this paper.

law of large numbers when the number of firms becomes very large and individual firms become very small.

Organization. The remainder of this paper is organized as follows. Section 2 presents the main model with oligopolistic competition, firm heterogeneity, and asymmetric supply shocks. Section 3 documents the existence of asymmetric supply shocks in firm-level data and estimates moments that can be used to calibrate the model. Section 4 uses to model to quantify the aggregate effects of asymmetric supply shocks and to study how the aggregate effects change with a higher intensity of competition among firms. Section 5 concludes.

2 A Model with Asymmetric Supply Shocks

In this section, I build a general equilibrium model with oligopolistic competition and firm heterogeneity. The purpose of the model is to introduce asymmetric supply shocks and study their firm-level and aggregate effects.

2.1 Environment

The model consists of a three-layer production structure, building on Atkeson and Burstein (2008), as well as a representative household.

2.1.1 Production

Time is discrete and indexed by t. The supply side consists of a large number of industries, J. Within each industry $j \in \{1, ..., J\}$, there are N_j firms, which are indexed by $i \in \{1, ..., N_j\}$. Each firm ij produces an intermediate good y_{ij} according to a constant-returns-to-scale production technology

$$y_{ijt} = \underbrace{Z_t^A Z_{jt}^I z_{ijt}^F z_{ijt}^X}_{z_{ijt}} l_{ijt} \tag{1}$$

where z_{ijt} is firm-specific productivity and l_{ijt} is the labor input. Productivity should be interpreted as a reduced-form way to capture a variety of factors. Importantly, firm-specific productivity is driven by four productivity components, namely aggregate productivity Z_t^A, industry-specific productivity Z_{jt}^I, firm-specific productivity z_{ijt}^F, and the asymmetric productivity component z_{ijt}^X. Aggregate, industry-specific, and firm-level productivity follow

AR(1) processes in logs:

$$\log Z_t^A = \rho_z^A \log Z_{t-1}^A + \sigma_z^A \epsilon_t^A \qquad \text{with } \epsilon_t^A \sim \mathcal{N}(0,1) \tag{2}$$
$$\log Z_{jt}^I = \rho_z^I \log Z_{jt-1}^I + \sigma_z^I \epsilon_{jt}^I \qquad \text{with } \epsilon_{jt}^I \sim \mathcal{N}(0,1) \tag{3}$$
$$\log z_{ijt}^F = \rho_z^F \log z_{ijt-1}^F + \sigma_z^F \epsilon_{ijt}^F \qquad \text{with } \epsilon_{ijt}^F \sim \mathcal{N}(0,1) \tag{4}$$

The asymmetric productivity component reflects an underlying asymmetric productivity component, z_t^X, which itself follows an AR(1) in logs, to which firms are differently exposed

$$z_{ijt}^X = \alpha_{ij} \times z_t^X \quad \text{where} \tag{5}$$
$$\log z_t^X = \rho_z^X \log z_{t-1}^X + \sigma_z^X \epsilon_t^X \qquad \text{with } \epsilon_t^X \sim \mathcal{N}(0,1) \tag{6}$$

The firm-specific exposure to the underlying asymmetric productivity component is captured by the exposure parameter α_{ij}.

Microfoundations. There is a wide range of possible microfoundations for asymmetric supply shocks. Since the mechanisms emphasized below are not specific to any particular shock, I remain with this general formulation of asymmetric supply shocks. Nonetheless, two microfoundations help to build intuition. First, the asymmetric supply shock could reflect a regional shock, such as a natural disaster. Firms located in an affected region are exposed ($\alpha_{ij} \neq 0$), while firms located elsewhere are not exposed ($\alpha_{ij} = 0$). Second, the asymmetric supply shock could reflect financial shocks. Some firms, which require external finance are exposed to changes in lending conditions, whereas other firms have sufficient internal finance and are not. Both of these examples are spelled out in more detail, alongside numerous other examples in Appendix B.1.

Aggregation. Industry output, Y_{jt}, is a CES aggregate of the intermediate goods y_{ijt} produced by the N_j firms in industry j

$$Y_{jt} = N_j^{\frac{1}{1-\rho}} \left[\sum_{i=1}^{N_j} y_{ijt}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \quad \text{with} \quad \rho > 1 \tag{7}$$

where the term $N_j^{\frac{1}{1-\rho}}$ neutralizes love of variety effects, as in De Loecker et al. (2021).[3,4] The parameter ρ captures the elasticity of substitution *within* industries. Aggregate output, Y_t^C, is a CES aggregate of industry output

$$Y_t^C = J^{\frac{1}{1-\eta}} \left[\sum_{j=1}^{N_J} Y_{jt}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \quad \text{with} \quad \eta > 1 \tag{8}$$

where again, love of variety effects are neutralized.[5] The parameter η captures the elasticity of substitution *across* industries.

Firm Optimization. Intermediate good firms take their productivity as given and maximize profits, d_{ijt}, which are defined by

$$d_{ijt} = \left(\frac{p_{ijt}}{P_t^C} \right) y_{ijt} - w_t l_{ijt} \tag{9}$$

where p_{ijt} is the price charged by firm i in industry j, P_t^C is the price index for the final consumption good (the numeraire), and w_t is the real wage. Firms compete by choosing quantities (Cournot competition) and take their competitors' productivity and optimal behavior into account.[6] They face the demand curve

$$\frac{p_{ijt}}{P_t^C} = \left(\frac{y_{ijt}}{Y_{jt}} \right)^{-1/\rho} \left(\frac{Y_{jt}}{Y_t^C} \right)^{-1/\eta} N_j^{-1/\rho} \tag{10}$$

which results from optimizing behavior of industry and consumption good producers. Under optimal behavior, firms set a (gross) markup over marginal costs, μ_{ijt}, which depends on their market share within the industry

$$s_{ijt} = \frac{p_{ijt} y_{ijt}}{P_{jt} Y_{jt}} \tag{11}$$

[3] This becomes relevant in Section 4.3 when the benefits of more competition are discussed. For all other exercises, this term is a constant as the number of firms in any industry is constant.

[4] The price index for the industry good is given by $P_{jt} = N_{jt}^{\frac{1}{\rho-1}} \left[\sum_{i=1}^{N_j} p_{ijt}^{1-\rho} \right]^{\frac{1}{1-\rho}}$ where p_{ijt} is the price of the intermediate good produced by firm i in industry j.

[5] The price index for the final consumption good is given by $P_t^C = J^{\frac{1}{\eta-1}} \left[\sum_{j=1}^{J} P_{jt}^{1-\eta} dj \right]^{\frac{1}{1-\eta}}$ where P_{jt} is the price index for industry j.

[6] I assume that firms do not internalize their effect on aggregates, as would be the case with $J \to \infty$. This follows Burstein et al. (2020) who show that relaxing this assumption has negligible quantitative consequences.

$$\frac{p_{ijt}}{P_t^C} = \mu_{ijt}(s_{ijt}) \frac{w_t}{z_{ijt}} \tag{12}$$

The optimal markup is a function of the market share because the demand elasticity is

$$\mu_{ijt}(s_{ijt}) = \frac{\epsilon_{ijt}(s_{ijt})}{\epsilon_{ijt}(s_{ijt}) - 1} \qquad \text{where} \qquad \epsilon_{ijt}(s_{ijt}) = \left[\frac{1}{\eta} s_{ijt} + \frac{1}{\rho}(1 - s_{ijt})\right]^{-1} \tag{13}$$

The demand elasticity, η is a weighted harmonic average of the elasticity of substitution across industries, η, and the elasticity of substitution within industries, ρ. This reflects that firms compete both *within* industries, where the relevant elasticity of substitution is ρ, and *across* industries, where the relevant elasticity of substitution is η. Firms internalize that their actions affect not only their own demand, but also demand for the industry good. The weight given to the elasticity of substitution across industries, η, is the market share of the firm within the industry. This reflects that when the firm is larger, it has a larger influence on industry demand. Therefore, the demand elasticity depends on the market share.

It is helpful to rewrite the optimal markup (equation 13) as

$$\mu_{ijt} = \frac{\rho}{\rho - 1} \left[1 - \frac{\frac{\rho}{\eta} - 1}{\rho - 1} s_{ijt}\right]^{-1} \tag{14}$$

and combine the definition of the market share (equation 11) with the price equation (equation 13) and the demand curve (equation 10) to get

$$s_{ijt} = \frac{z_{ijt}^{\rho-1} \mu_{ijt}^{1-\rho}}{\sum_{k=1}^{N_j} z_{kjt}^{\rho-1} \mu_{kjt}^{1-\rho}} \tag{15}$$

Given the firm-specific component z_{ijt} for all firms i, equations (14) and (15) can be used to solve for all firms' market shares, s_{ijt}, and markups, μ_{ijt}, in period t. Importantly, this is possible irrespective of the specific distribution of firm-specific components, z_{ijt}. [Maybe mention that it is really the entire distribution that matters?]

Aggregation. Having solved for the equilibrium in each industry, we can combine the distribution of market shares with firm-level markups productivities to derive industry-level and aggregate values. The industry markup, defined by $\mu_{jt} = \frac{(P_{jt}/P_t^C)Y_{jt}}{w_t L_{jt}}$, can be rewritten as a market share-weighted geometric average of the firm-level markups[7]:

$$\mu_{jt} = \left[\sum_{i=1}^{N_j} \mu_{ijt}^{-1} s_{ijt} \right]^{-1} \tag{17}$$

Industry productivity can be computed as

$$Z_{jt} = \frac{Y_{jt}}{L_{jt}} = \frac{N_j^{\frac{1}{1-\rho}} \left[\sum_{i=1}^{N_j} \mu_{ijt}^{1-\rho} z_{ijt}^{\rho-1} \right]^{\frac{\rho}{\rho-1}}}{\sum_{i=1}^{N_j} \mu_{ijt}^{-\rho} z_{ijt}^{\rho-1}} \tag{18}$$

where $N_j^{\frac{1}{1-\rho}}$ is the term arising from the cancellation of love of variety effects. Aggregation from industry-level variables to aggregate variables (μ_t, Z_t) proceeds analogously.

2.1.2 Household

There is a representative household which consumes the final consumption good, C_t, supplies labor, L_t, and owns all firms in the economy. The household has Epstein-Zin preferences and maximizes

$$W_t = u(C_t, L_t) + \beta \left(\mathbb{E}_t W_{t+1}^{1-\alpha} \right)^{1/(1-\alpha)} \tag{19}$$

where the risk aversion parameter α allows specifying a coefficient of relative risk aversion which differs from the inverse of the intertemporal elasticity of substitution.[8] The period utility function is standard,

$$u(C_t, L_t) = \frac{C_t^{1-\sigma}}{1-\sigma} + \psi \frac{(1-L_t)^{1-\chi}}{1-\chi} \tag{20}$$

The household maximizes (19) subject to a sequence of budget constraints

$$C_t = w_t L_t + D_t \tag{21}$$

[7] Alternatively, the industry markup can be represented as a function of the Herfindahl–Hirschman index (HHI), a measure of industry concentration

$$\mu_{jt} = \frac{\rho}{\rho-1} \left[1 - \frac{\frac{\rho}{\eta} - 1}{\rho - 1} HHI_{jt} \right]^{-1} \tag{16}$$

where the HHI is calculated as the sum of squared market shares, $HHI_{jt} = \sum_{i=1}^{\widetilde{N_{jt}}} s_{ijt}^2$.

[8] In the current calibration, $\alpha = 0$, such that the coefficient of relative risk aversion coincides with the inverse of the intertemporal elasticity of substitution and Epstein-Zin preferences coincide with standard expected utility preferences.

where D_t subsumes dividends of all firms. Optimization gives rise to a standard wage-Euler equation

$$C_t^{\sigma} \psi (1 - L_t)^{-\chi} = w_t \tag{22}$$

2.2 Discussion: Asymmetric Supply Shocks vs. Other Supply Shocks

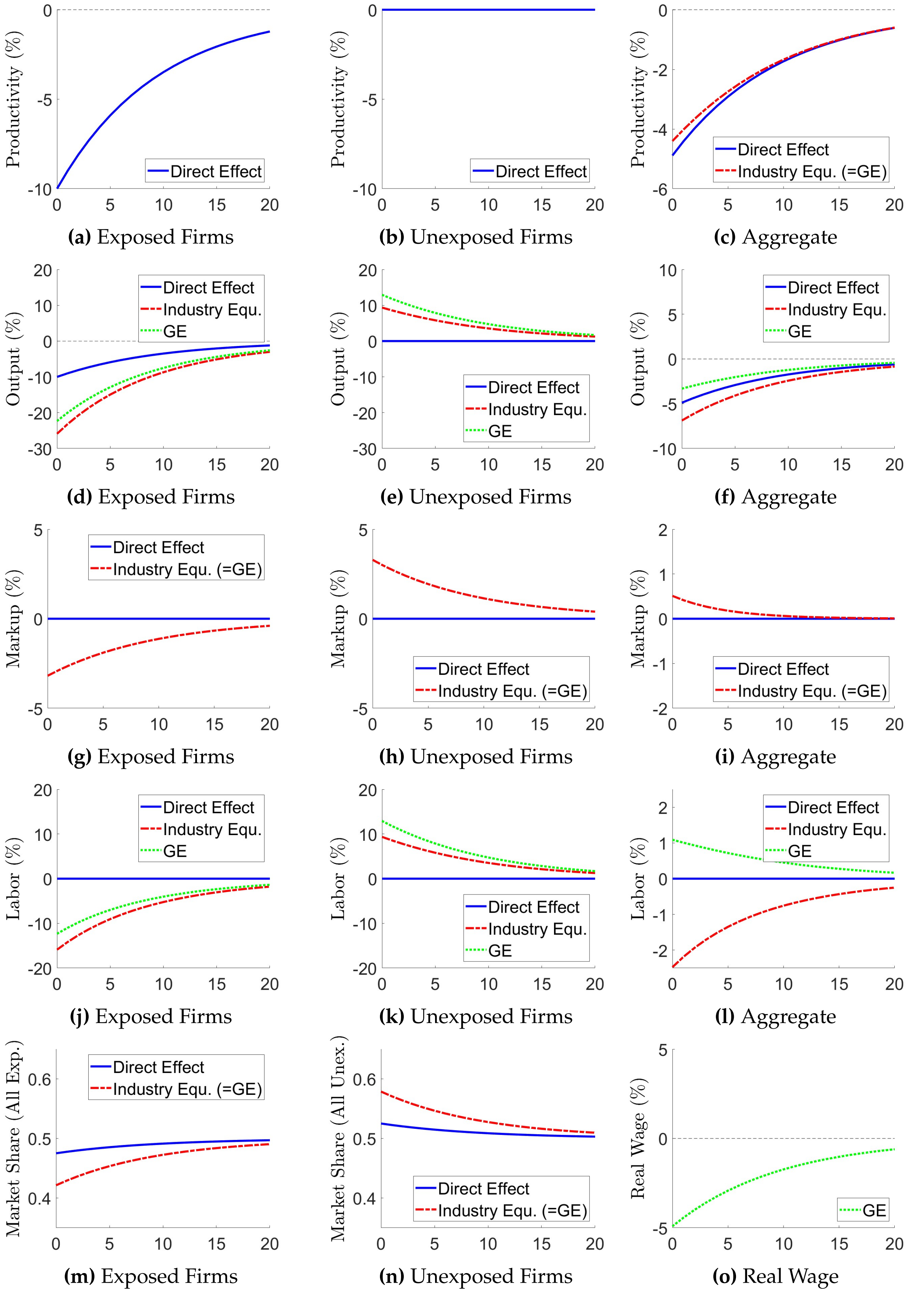
All four supply shocks in the model (aggregate, industry-specific, asymmetric, firm-level) are able to generate fluctuations in aggregate output. However, aggregate and industry-specific shocks have identical effects on all firms in any given industry. Therefore, they do not affect the distribution of firm-specific productivity within industries and hence neither the distributions of firm-level output, market shares, and markups. In contrast, firm-specific shocks and asymmetric supply shocks change the distribution of firm-specific productivity within industries and can therefore rationalize fluctuations in the distribution of firm-level output, which are observable in the data.

Firm-specific and asymmetric supply shocks differ in two important ways. First, asymmetric supply shocks are able to generate aggregate fluctuations even as the number of firms diverges. Gabaix (2011) has shown that firm-specific shocks generate meaningful aggregate fluctuations only when there are some very big firms. Otherwise, firm-specific shocks "average out". In contrast, asymmetric supply shocks—as modeled above—affect all industries and a subset of firms and therefore generate aggregate fluctuations even if the number of industries or the number of firms within any industry diverges. Second, asymmetric supply shocks generate correlated fluctuations in the distribution of sales across industries. In contrast, firm-specific shocks do not generate a correlation across industries. I will exploit this difference to calibrate the model in Section 4.1.

2.3 Numerical Example

To build some intuition for the firm-level and aggregate effects of asymmetric supply shocks, I discuss a numerical example, using a simplified version of the model. I assume that all industries are symmetric and feature $N_j = 4$ firms with initially equal productivity levels. Of these firms, two are exposed to the asymmetric supply shock ($\alpha = 1$), while the other two are not ($\alpha = 0$).

A 10% negative asymmetric supply shock decreases the productivity of the exposed firms by 10% while leaving the productivity of the unexposed firms unchanged, as shown in Panels (a) and (b) of Figure 1. Panel (c) shows that due to this *direct* effect, aggregate productivity falls by 5%. The direct effects on firm-level and aggregate output equal the direct effects on productivity and are shown in Panels (d) - (f).



(a) Exposed Firms **(b)** Unexposed Firms **(c)** Aggregate

(d) Exposed Firms **(e)** Unexposed Firms **(f)** Aggregate

(g) Exposed Firms **(h)** Unexposed Firms **(i)** Aggregate

(j) Exposed Firms **(k)** Unexposed Firms **(l)** Aggregate

(m) Exposed Firms **(n)** Unexposed Firms **(o)** Real Wage

Figure 1: Asymmetric Supply Shock – Aggregate Effects

Notes: The x-axis depicts time periods in years. The y-axis depicts percent deviations from steady state (100 x log), except for market shares which are shown in levels.

As highlighted before, what distinguishes asymmetric supply shocks from aggregate and industry-specific shocks is that they change the distribution of market shares within industries. There is some reallocation of market shares due to the direct effect, but also amplification due to the strategic responses of all firms to the shock, as shown in Panels (m) and (n). These strategic responses are discussed next.

In consequence of the direct effect, exposed firms produce 10% less output and need to charge a 10% higher price (to hold the markup constant). At that price, however, demand has fallen substantially more than 10%. Hence, they have excess supply and respond by reducing the markup and labor input and production. The unexposed firms, in contrast, face excess demand and respond by doing the opposite, they increase their markups as well as labor and output (Panels h, n, k). When both demand and supply for all firms' goods are in equilibrium again ("Industry Equilibrium"), aggregate output has fallen even more (Panel f). As shown in panel (l), this is because the unexposed firms only partially make up for the drop in labor of the exposed firms. At the same time, the drop in aggregate productivity is dampened by the reallocation of resources from unproductive to productive firms. This also implies a reallocation from low-markup firms to high-markup firms, so that the aggregate markup rises, as shown in Panel (i). Section 4.3 shows that this *strategic response* is stronger when firms have less market power.

Finally, the lower aggregate productivity and higher markup lead to a lower real wage, as shown in Panel (o). In general equilibrium, the household increases its labor supply, increasing firm-level and aggregate output.

3 Measuring Asymmetric Supply Shocks in the Data

Identifying asymmetric supply shocks in aggregate data is challenging, because there may be several of them and the effects on aggregate variables are not all unambiguous.[9] Therefore, I use firm-level data to document the existence of asymmetric supply shocks and ultimately calibrate the model.

3.1 Data

I use annual firm-level data from Compustat North America from 1990 to 2019. The data treatment is described in detail in Appendix A.1. Despite Compustat capturing a non-representative sample of firms, I confirm in Appendix A.2 that aggregate dynamics of these firms are highly correlated with the aggregate dynamics from national accounts data.

[9] For example, in the numerical example (Figure 1) in Section 2.3, both positive and negative shocks *raise* the aggregate markup. This non-linearity is shown more directly in Figure 3, see also Burstein et al. (2020).

The main variable of interest is firm-level sales. In contrast to actual output, sales are directly observable from the data. To deal with autocorrelation, I estimate an AR(1) process and remove a firm-fixed effect[10]:

$$\log(sales_{ijt}) = \beta_{ij} + \rho \times \log(sales_{ijt-1}) + \epsilon_{ijt} \tag{23}$$

Henceforth, I use the estimated firm-specific residuals ($\widehat{\epsilon_{ijt}}$) to investigate the drivers of fluctuations.

3.2 Identification

Through the lens of the model, the firm residuals reflect all four shocks. By regressing the residuals on time fixed effects and industry-by-time fixed effects, aggregate and industry-specific shocks are straightforward to identify—they affect sales of all firms (in a given industry) identically—and control for. The residuals from these regressions reflect only firm-specific and asymmetric supply shocks and are thus informative about the joint importance of these two shocks.

To differentiate between firm-specific and asymmetric supply shocks, I exploit that asymmetric supply shocks induce a correlation of firm-level residuals across industries, while firm-specific shocks do not. A straightforward method to find out how much variation in firm residuals can be explained by one or several common components is principal component analysis. I estimate

$$\begin{bmatrix} \widehat{\epsilon}_{i=1,t=1} & \cdots & \widehat{\epsilon}_{i=N,t=1} \\ \vdots & \ddots & \\ \widehat{\epsilon}_{i=1,t=T} & & \widehat{\epsilon}_{i=N,t=T} \end{bmatrix} = F \times \Lambda + \nu \tag{24}$$

where the data matrix combines the residuals from all N firms in all T time periods. F is a $T \times k$ matrix containing k unobserved factors, Λ is a $k \times N$ matrix of factor loadings, and ν is a $T \times N$ matrix of residuals. The factors correspond to the underlying asymmetric productivity components in the model, the loadings to the exposure coefficients, and the residuals to the firm-specific shocks.

If firm residuals were caused exclusively by firm-level shocks, the principal components should explain barely any variation (in a large enough sample), because firm-specific shocks affect firms in only one industry. In contrast, if firm residuals also reflect asymmetric supply shocks, the first principal component(s) will explain a relevant share of the variation. This

[10]For this step, I drop firms with fewer than 5 observations in the data.

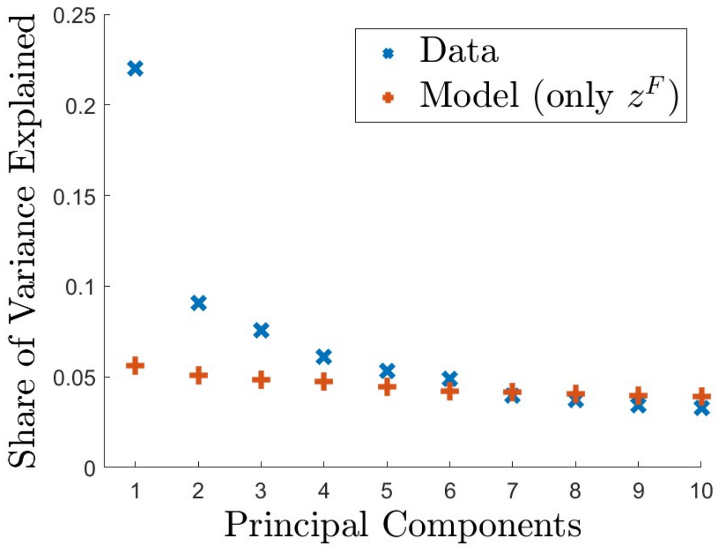


Figure 2: Share of Firm Sales Residuals Explained by Principal Components

Notes: Dataset is a balanced sample from 1990 - 2019 (T=29) with N=962 unique firms in J=179 industries. The model is as described above and as calibrated below with only firm-level shocks.

share will eventually be used to calibrate asymmetric supply shocks in the model.

3.3 Results

The standard deviation of firm residuals from Equation (23) is 0.477. After regressing these residuals on time and industry-by-time fixed effects, the standard deviation falls to 0.462. Hence, a substantial amount of fluctuations in firm-level sales growth *cannot* be explained by aggregate or industry-specific shocks.

To implement the principal component analysis, I restrict the sample to firms that are in the dataset for the whole sample, in order to avoid having to deal with missing observations. This sample contains a total of $N = 962$ firms in $J = 179$ SIC-3 industries, observed for $T = 29$ years. The results are plotted in Figure 2. The first principal component explains around 22% of the variance, the second one 9%, and the third one 7.5%. This is clear evidence for the existence of asymmetric supply shocks.

Figure 2 compares the share of variance explained by the first ten principal components with the shares that they would explain in a model with only firm-specific shocks. These hypothetical shares are not zero, because the dimensions of the dataset are limited, in particular because only 29 years are available. Nonetheless, the comparison clearly speaks to the existence of asymmetric supply shocks.

4 Quantitative Model Analysis

In this section, I calibrate the model presented in Section 2, using the data and analysis described in Section 3. The purpose is to quantify the aggregate fluctuations that can be attributed to asymmetric supply shocks (Section 4.2) and assess how a higher degree of competition among firms affects macroeconomic outcomes (Section 4.3).

4.1 Calibration

I calibrate the model to the U.S. economy. One model period corresponds to one year. I begin by fixing a number of parameters to conventional values. These fixed parameters are listed in Table 1.

The labor disutility parameter, ψ, is chosen such that in steady state the household spends a third of its time endowment working. The curvature of the utility function with respect to consumption is set to $\sigma = 2$, which implies an intertemporal elasticity of substitution (IES) of 0.5. The curvature of the utility function with respect to labor is set to $\chi = 3$, which implies a Frisch elasticity of labor supply of 2/3 (Rudebusch and Swanson, 2012).

The number of industries is set to $J = 179$ as in the balanced panel of the Compustat data. In the current calibration, all industries are ex-ante homogeneous, and ex-post heterogeneity results only from realizations of shocks. The number of firms per industry is set to $N = 5$ which brings the model as close as possible to the balanced-panel Compustat data (962/179 = 5.37 firms per industry).[11] The elasticity of substitution within industries is set to $\rho = 10$ (Atkeson and Burstein, 2008; Mongey, 2021; Wang and Werning, 2022). The elasticity of substitution across industries is set to $\eta = 1.4$ to generate an average markup of around 1.3 (Mongey, 2021).[12]

The number of asymmetric supply shocks is set to $N_X = 3$, based on the evidence, shown in Figure 2, that there are at least three common components to the firm residuals. The exposure coefficients for the asymmetric supply shocks are set to be drawn from a normal distribution, based on the distribution of factor loadings, plotted in Figure A.2. The exposure coefficients from the three asymmetric supply shocks are drawn independently, as the loadings are uncorrelated in the data. The mean of the normal distributions needs to be 0, as otherwise the effects would be absorbed by fixed effects. The standard deviation of the distributions is normalized to 1, while the standard deviation of the asymmetric supply shocks

[11] Of course, 962 firms are a tiny subset of the total number of firms in the economy. Nonetheless, these firms, being the public firms, make up a large share of GDP.

[12] The average markup is a function mainly of the two elasticities of substitution and the number of firms per industry. N and ρ being fixed already, the markup is therefore informative about η. See Mongey (2021) for a discussion of the empirical evidence on the average markup in the U.S. economy.

will be calibrated internally below. The persistence of the asymmetric supply shocks is set to $\rho_X = 0.9$, reflecting the average persistence of the three common components (see Appendix A.3).

Param.	Description	Value	Target / Source
Household			
ψ	Labor disutility	1.8	$L \approx 1/3$
σ	Curvature of util. w.r.t. C	2	IES = 0.5
χ	Curvature of util. w.r.t. L	3	Frisch elasticity = 2/3
Firms			
J	Number of industries	179	Compustat data (balanced panel)
N	Number of firms per industry	5	Compustat data (balanced panel)
ρ	Elast. of subst. within ind.	10	Atkeson and Burstein (2008)
η	Elast. of subst. across ind.	1.4	Avg. markup $\approx$ 1.3 (Mongey, 2021)
Exogenous Processes			
N_X	Number of asym. supply shocks	3	PCA evidence (Compustat)
σ^α	Std. dev. of exposure coeff.	1	Normalization
ρ_z^X	Persistence of asym. supply shocks	0.9	PCA evidence (Compustat)

Table 1: Calibration: Fixed Parameters

The remaining model parameters are calibrated internally to match moments of the micro data. The calibrated parameters as well as targeted moments are listed in Table 2. Even though all parameters are calibrated jointly, it is informative to describe which moments are particularly informative about which parameter. The standard deviation of firm residuals is informative about the volatility of firm-specific and asymmetric supply shocks. The share of this volatility that is explained by the first three common components is informative about the relative importance of the two shocks. Finally, the autocorrelation of firm residuals is informative about the persistence of firm-specific shocks.

Param.	Description	Value	Target	Data	Model
Exogenous Processes					
σ^X	Std. dev. of asym. sup. shocks	0.0331	Share of firm vol. explained	38.6%	38.6%
σ^I	Std. dev. of firm-spec. shocks	0.0900	Std. dev. of firm residuals	0.46	0.46
ρ^I	Persist. of firm-spec. shocks	0.5624	Autocorr. of firm residuals	0.72	0.72

Table 2: Calibration: Fitted Parameters

4.2 Aggregate Effects of Asymmetric Supply Shocks

Having calibrated the model to the U.S. economy, it is straightforward to compute the aggregate volatility that arises with this model which only features firm-level and asymmetric supply shocks. The simulation procedure is described in Appendix B.4.

Table 3 shows that the model explains about 38% of fluctuations in aggregate output. The remaining 62% would therefore be ascribed to industry-specific and aggregate shocks, which are shut off in the current calibration of the model. The results are similar for aggregate labor as the model explains about 27% of fluctuations observed in the data. At the same time, the model explains the bulk of fluctuations in the labour share (76%).

To isolate the contribution of asymmetric supply shocks to the aggregate fluctuations, I set their volatility to 0 (third row of Table 3). Hence, the model only features firm-level shocks. Evidently, asymmetric supply shocks are more important for aggregate fluctuations than firm-specific shocks. The former explain about 28% of fluctuations in aggregate output (firm-specific shocks: 11%) and 24% of fluctuations in aggregate labor (firm-specific shocks: 4%). In addition, they explain about 68% of fluctuations in the labor share (firm-specific shocks: 8%).

	$\sigma(Y)$	$\sigma(L)$	$\sigma(LaborShare)$	$\sigma(z_{ijt})$
Data	1.41%	1.65%	0.85%	
Model	0.56%	0.47%	0.65%	16.8%
$\rightarrow \sigma^X = 0$	0.16%	0.07%	0.07%	10.8%

Table 3: Aggregate Fluctuations

Notes: Data moments are computed from annual data from 1947-2019. All moments are computed after HP-filtering ($\lambda = 6.25$) the data in logs.

4.3 The Intensity of Competition

The aggregate consequences of asymmetric supply shocks can be thought of as reflecting three effects. First, there is the *direct effect*, i.e., the productivity of a subset of firms changes. The magnitude of the direct effect does not depend on the number of firms, because the distribution of exposure coefficients remains unchanged. Second, there is a *strategic response*. The direct effect changes demand curves for both exposed and unexposed (or, more and less exposed) firms, inducing them to adjust their production and prices. This strategic response depends on features of the distribution of firms and in particular on the intensity of competition among firms. This section will analyze how the strategic response changes with a higher number of firms. Third, there is a *general equilibrium effect*, as the household reacts to changes in aggregate productivity and the aggregate markup. For a given change in productivity and the markup, this effect is independent of features of the distribution of firms.

Numerical Example. To illustrate how the *strategic response* changes when there is a higher intensity of competition among firms (i.e., a higher number of firms), I re-use the numerical

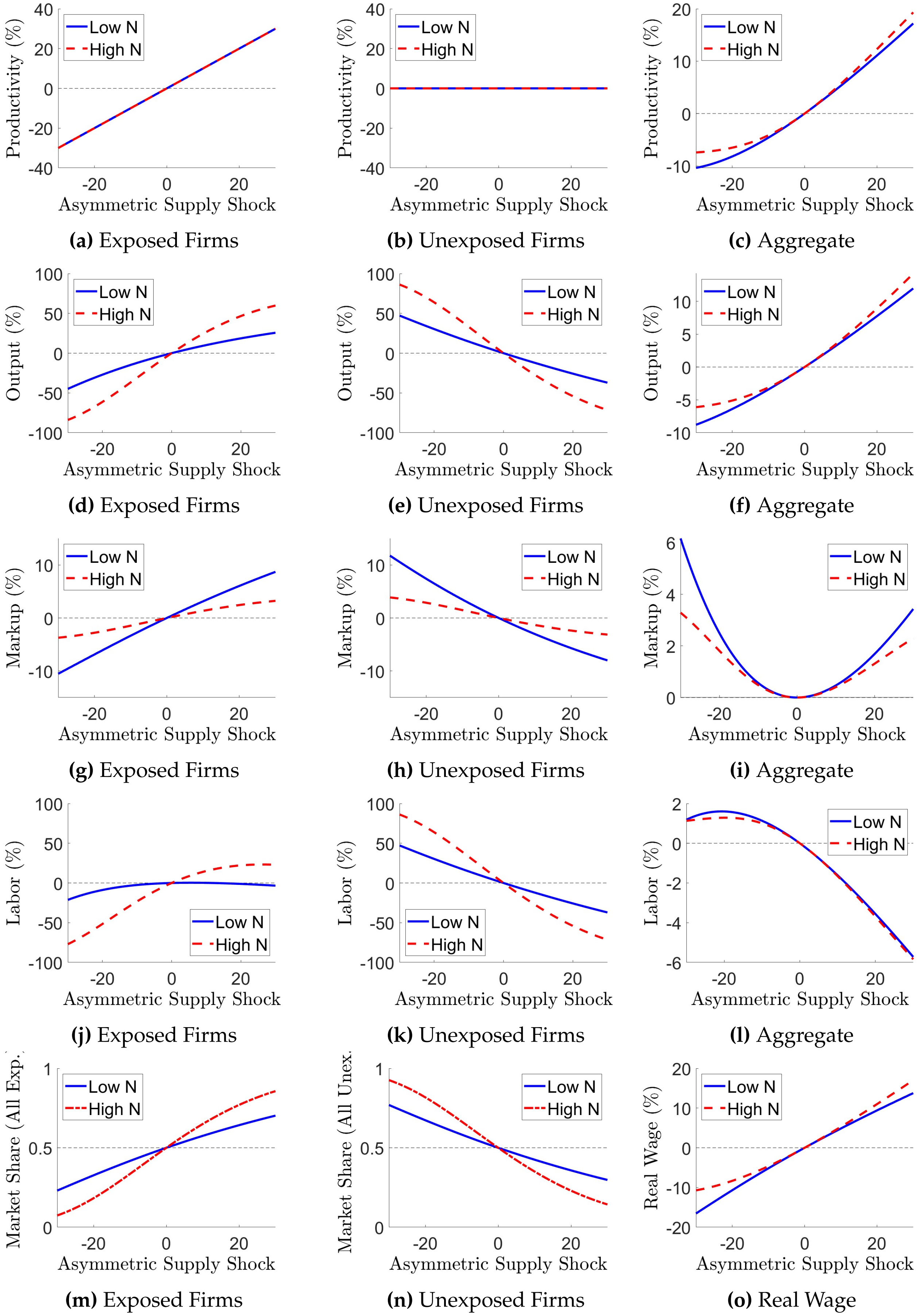


Figure 3: Asymmetric Supply Shocks – Low & High Competition

Notes: The x-axis depicts the size of the asymmetric supply shock. The y-axis depicts percent deviations from steady state, except for market shares which are shown in levels. The low-competition (high-competition) economy features 4 (16) firms.

example presented in Section 2.3 (Figure 1). As in that section, the economy consists of a large number of industries with ex-ante identical firms. The economy is hit by an asymmetric supply shock of size -30% to +30% (x-axis). I only consider the effect in the impact period and contrast economies with 4 firms per industry (as in Section 2.3; blue lines) and 16 firms per industry (red lines). In either economy, half of all firms are exposed, such that the direct effect remains the same. I investigate deviations from steady state, such that the well-known steady-state benefits of a higher intensity of competition (i.e., lower markups) do not play a role.

Figure 3 illustrates two implications of a higher intensity of competition. First, facing asymmetric supply shocks, in an economy with a higher number of firms, productivity and output are *higher on average*, but potentially also *more volatile*. Second, the markup can be higher or lower on average and more or less volatile. Both implications reflect the change in the strategic response of firms.

When the exposed firms are hit with a negative shock and the unexposed firms, in consequence, face more demand, they hire more labor (Panel k), produce more output (Panel e), and raise their markups (Panel h). However, with a higher intensity of competition, they raise production relatively more and markups relatively less. The reason is that with a higher number of firms, firms have relatively little market power (i.e. a high demand elasticity), which also increases only slightly due to the shock. In contrast, when the intensity of competition is low and firms have a lot of market power, they can increase their markups a lot more. This strategic behavior also matters for the reallocation from exposed to unexposed firms, evidenced by the changes in market shares (Panels m, n). With a higher intensity of competition, there is a faster reallocation which leads to a smaller drop in aggregate productivity (Panel c) and aggregate output (Panel f). The mechanics are similar for positive asymmetric supply shocks. With a higher intensity of competition, again, the reallocation from low-productivity (here unexposed) firms to high-productivity (here exposed) firms proceeds faster and the firm-level changes in markups are smaller.

For the response of aggregate productivity to asymmetric supply shocks, only the reallocation from low-productivity to high-productivity firms matters, which is unambiguously stronger with a higher intensity of competition. This means that in the face of asymmetric supply shocks, productivity is higher on average, but potentially also more volatile. For the response of the aggregate markup, both the between-firm reallocation and the within-firm markup changes matter. A higher intensity of competition strengthens the reallocation, making the aggregate markup higher on average and more volatile. In contrast, more competition reduces within-firm markup changes, making the aggregate markup lower on average and less volatile. In Panel (i) of Figure 3, the latter effect dominates, though quantitatively, this could be different.[13] I now assess the implications of a higher intensity of competition in the quantitative model.[14]

Quantitative Results. Table 4 shows the results from model simulations with the baseline calibration (5 firms per industry) and a high-competition calibration (20 firms). Steady-state aggregate productivity is identical because there are no love-of-variety effects. The steady-state (gross) markup is well-known to be lower when there are more firms because individual firms have less market power. The lower aggregate markup in turn leads to a higher real wage, higher labor input, and hence higher steady-state output by around 3%. The presence of asymmetric supply shocks (and also firm-specific shocks) generates fluctuations in aggregate variables around their steady-state values. The shock processes are symmetric, but the economy's response to these shocks is asymmetric, as illustrated in Figure 3. The source of this asymmetry is the strategic response of firms.

	Steady State			Average (relative to SS)			Standard Deviation		
	Y	Z	μ	Y	Z	μ	Y	Z	μ
Baseline ($N = 5$)	0.35	1	1.29	3.00%	5.77%	4.07%	0.56%	1.03%	0.65%
High Competition ($N = 20$)	0.36	1	1.15	5.98%	9.63%	3.58%	1.00%	1.61%	0.57%

Table 4: Macroeconomic Consequences of Higher Intensity of Competition

Notes: Steady-state values are reported in levels. Deviations of average values from steady-state values are reported in percent (100 x dlog). Standard deviations are computed after HP-filtering ($\lambda = 6.25$) the values in logs.

With a higher number of firms, there is a better reallocation from low-productivity to high-productivity firms, which implies that aggregate productivity benefits more from positive shocks and suffers less from negative shocks. Average productivity rises by 9.6%, relative to its steady-state value, with 20 firms, and by 5.8% with 5 firms. In addition, the average markup rises above its steady-state value, but this increase is smaller with 20 firms than with 5 firms (3.6% vs. 4.1%), as the dampened within-firm markup changes dominate the stronger between-firm reallocation. In either economy, average output exceeds steady-state output, as the increase in productivity dominates the increase in the markup. However, with 20 firms, this increase in average output is substantially larger (6% vs. 3%) as average productivity rises more and the average markup rises less.

However, the beneficial effects of a higher number of firms in the face of asymmetric supply shocks—higher average productivity, lower average markup, higher average output—

[13] Burstein et al. (2020) provide analytical results on the effects of firm-specific shocks on the aggregate markup and discuss the within-firm changes and between-firm reallocation.

[14] In a previous version of this paper, I derive some analytical results of a higher number of firms per industry.

do not come without a cost. The same asymmetry that improves the *average* state of the economy, also raises the *volatility* of productivity by around 56%, compared with the economy with only 5 firms. At the same time, the volatility of the aggregate markup falls by around 12%.[15] Again, the effect on productivity dominates, such that the volatility of aggregate output increases by 78%. In sum, the optimal number of firms needs to trade off a better average state of the economy with a higher volatility of output.

5 Conclusion

In this paper, I study the aggregate effects of asymmetric supply shocks. These are disruptions, such as regional or financial shocks, that affect some firms more than others within many industries. Even though they may directly only affect a subset of firms, they trigger a strategic response from all firms. Relying on a heterogeneous-firm model with imperfect competition, calibrated to moments of U.S. firm-level data, I show that asymmetric supply shocks can account for around a quarter of fluctuations in aggregate output. In addition, I show that a higher intensity of competition makes aggregate output more volatile, but higher on average.

I emphasize that the main mechanism is relevant for all supply disruptions that change the distribution of sales shares among firms within industries. A broad class of models with firm heterogeneity gives rise to such disruptions, thereby providing micro-foundations for asymmetric supply shocks. Some well-known examples include models with firm financial heterogeneity (Khan and Thomas, 2013; Ottonello and Winberry, 2020; Koby and Wolf, 2020), regional shocks (Atkeson and Burstein, 2008), or time-varying distributions of idiosyncratic shocks (Bloom et al., 2018; Salgado et al., 2019).

The highlighted consequences of a higher intensity of competition provide an additional reason why the secular increases in market power, markups, and industry concentration, documented by De Loecker et al. (2020) and Covarrubias et al. (2020), are potentially worrisome. They not only reduce consumer welfare in a static economy (Edmond et al., 2018) but also reduce the economy's ability to deal with asymmetric supply shocks, further reducing average output. Competition policy must take into account that by leaning against these trends, it can not only reduce markups but also affect the economy's ability to deal with exogenous shocks.

[15] It is worth highlighting that the mechanism for this is different from the one emphasized in Gabaix (2011). While in Gabaix (2011), a higher number of firms reduces aggregate volatility because firm-specific shocks average out, asymmetric supply shocks do not average out with a higher number of firms. The simulated model includes firm-specific shocks, which are however less relevant quantitatively, as shown in Table 3.

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Appendix

A Data Appendix

A.1 Data Treatment

I use annual firm-level data from Compustat North America. The data treatment described here broadly follows De Loecker et al. (2020) and Baqaee and Farhi (2020). From the beginning, I exclude

1. firms not incorporated in the United States (based on FIC)
2. observations with missing or non-classifiable industry (NAICS)
3. observations with missing or non-positive sales (SALE)

A.2 Compustat vs. National Accounts Data

The ultimate goal is to understand fluctuations in aggregate variables such as GDP. To do so, I investigate disaggregated data. Of course, the disaggregated firm-level data does not capture the entire economy. Therefore, it is important to confirm first of all that the disaggregated data displays the same dynamics as the aggregate data. Figure A.1 confirms that the growth rate of GDP is highly correlated with the growth rate of the sum of firm-level sales ($\rho = 0.8$). Moreover, it is highly correlated with average firm-level sales growth ($\rho = 0.86$).

A.3 Additional PCA Results

Figure A.2 plots the distribution of factor loadings for the first three factors. The pairwise correlations are very low ($-0.023, -0.018, -0.017$). Figure A.3 plots the factors themselves.

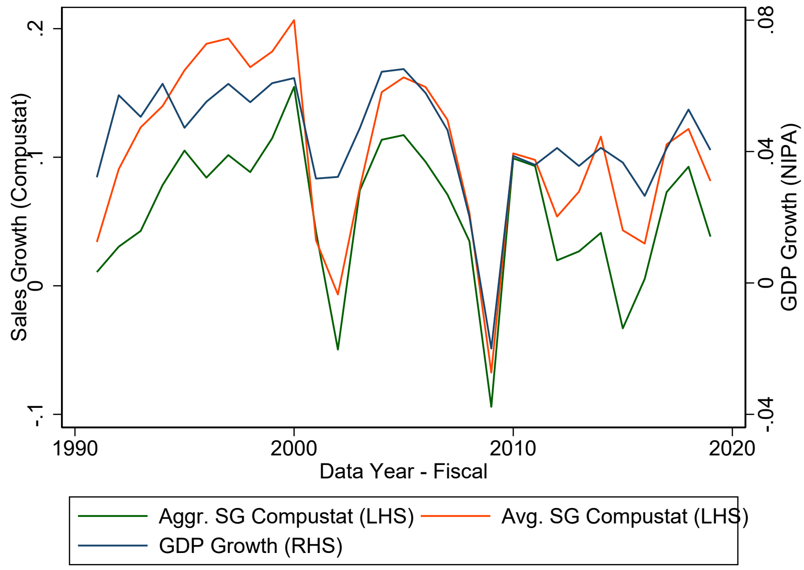
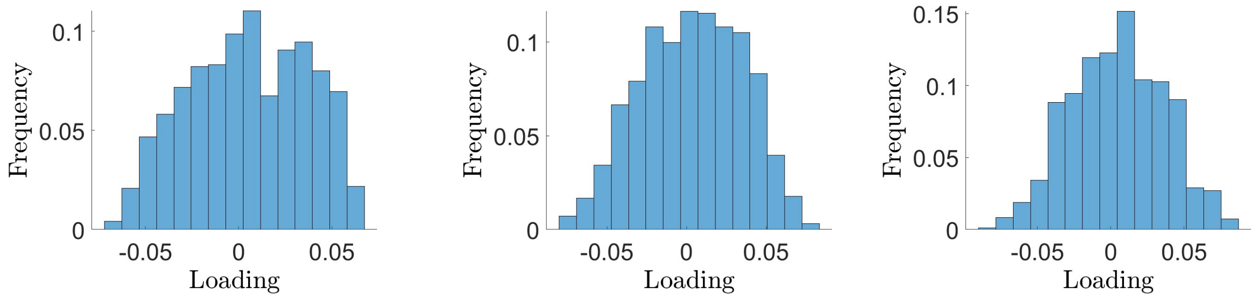


Figure A.1: Compustat vs. NIPA Data



(a) Factor 1 **(b)** Factor 2 **(c)** Factor 3

Figure A.2: Distribution of Factor Loadings

Their autocorrelations are 0.95, 0.91, and 0.84. Of course, the factors are only identified up to a rotation at this point.

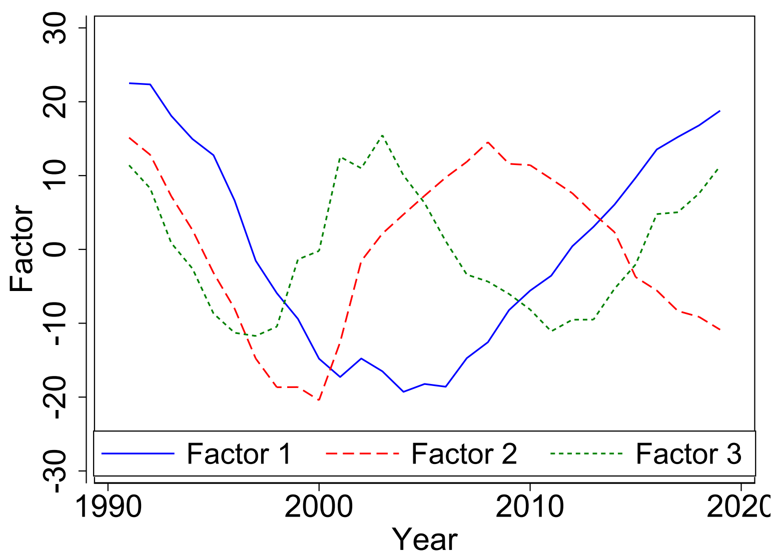


Figure A.3: Factors

B Model Appendix

B.1 Microfoundations for Asymmetric Supply Shocks

Asymmetric supply shocks are defined as shocks that, within many industries, affect one or more firms differently than one or more other firms and thereby change the distribution of sales across firms. In this section, I discuss a variety of examples of asymmetric supply shocks. First, I model regional shocks and financial shocks as explicit microfoundations. Thereafter, I discuss and organize some additional examples.

B.2 Example 1: Regional Shocks

Assume that the economy consists of R regions. In each region, production is occasionally impaired due to local events, such as adverse weather events (floods, earthquakes), strikes, or lockdowns. Hence, for each region $r \in R$, there exists a regional productivity component, z_{rt}, which can be interpreted as an asymmetric productivity component, as introduced in Section 2. Unless all firms from an industry are located in a single region, a regional shock affects some firms more than others, and thereby changes the distribution of sales within industries.

Each firm is exposed to the regional productivity component of its own region ($\alpha^r_{ij} = 1$), but not to the other ones ($\alpha^r_{ij} = 0$). In sum, the asymmetric productivity component of firm ij, located in region $r = k$ in period t is:

$$z^X_{ijt} = \sum_{r=1}^{R} \alpha^r_{ij} \times z_{rt} = 1 \times z^{r=k}_{rt} + 0 \times z^{r\neq k}_{rt} \tag{25}$$

B.3 Example 2: Financial Shocks

Assume that production not only requires labor but also capital k_{ijt}, which has a time-to-build of one period and therefore must be purchased in $t-1$. The production function is therefore

$$y_{ijt} = Z^A_t Z^S_{jt} z^I_{ijt} \underbrace{k^{\theta}_{ijt}}_{:=z^X_{ijt}} l_{ijt} \tag{26}$$

I further assume that in each industry, there are two groups of firms, financially constrained and financially unconstrained ones. Financially unconstrained firms can afford their optimal level of capital k^*_{ijt}, while financially constrained firms cannot afford their optimal level, so $k_{ijt} \leq \gamma_t k^*_{ijt}$ with $\gamma_t \in (0,1]$. The parameter γ_t reflects financial conditions, or, more explicitly the tightness of borrowing constraint, and fluctuates over time.

Now, financial conditions can be interpreted as an asymmetric productivity component, as introduced in Section 2. Unconstrained firms will always choose $k_{ijt} = k^*_{ijt}$. Normalizing ${k^*_{ijt}}^{\theta} = 1$, their asymmetric productivity component is $z^X_{ijt} = 1$ and hence unaffected by changes in γ_t. Constrained firms will always choose $k_{ijt} \leq \gamma_t k^*_{ijt}$ and therefore, their asymmetric productivity component is $z^X_{ijt} = \gamma_t^{\theta}$.

This example could easily extended from two types of firms to a continuum of exposure intensities, as in the model of Ottonello and Winberry (2020). In addition, in a framework like theirs, in which the borrowing constraint is forward-looking and depends on the future state of the economy, any aggregate shock has an asymmetric component, because it changes the tightness of borrowing constraints.

B.3.1 Further Examples.

There exists a fairly broad class of firm heterogeneity frameworks that give rise to supply disruptions that can be considered asymmetric supply shocks.

Heterogeneous Exposure. Many firm heterogeneity frameworks make some firms within an industry more exposed to certain disruptions than other firms. Three groups of examples appear particularly relevant. First, when firms in an industry are distributed across several regions, region-specific shocks, such as natural disasters, strikes or regional lockdowns, reallocate sales across regions and thus firms. In a framework with multiple countries, such as Atkeson and Burstein (2008), country-specific productivity shocks also belong to this category. Second, when firms in an industry use different inputs or have different production functions, they are differently exposed to changes in the price or the availability of inputs. Shortages of natural gas immediately only affect firms which use natural gas, instead of oil, as a source of energy. Lockdowns in some part of the world, such as China, only affect firms getting their inputs from this particular region. Moreover, firms with a relatively labor-intensive production process are more exposed to wage changes than relatively capital-intensive competitors. Third, firm-level frictions, in particular financial frictions as in Khan and Thomas (2013), Khan et al. (2016) and Ottonello and Winberry (2020), make firms differently exposed to aggregate shocks. Financial shocks to the tightness of borrowing constraints as in Khan and Thomas (2013) or Khan et al. (2016) immediately affect only firms which are "financially constrained", in contrast to "financially unconstrained" firms. A financial tightening would thus reallocate production and sales from constrained to unconstrained firms. Other aggregate shocks, such as monetary policy shocks in Ottonello and Winberry (2020), endogenously change the tightness of borrowing constraints and therefore set in motion the same mechanism.

Idiosyncratic Shocks. Idiosyncratic shocks to productivity, demand, capital quality, or some other firm-level state variable can be considered as a special case of asymmetric supply shocks. Idiosyncratic shocks reallocate market shares between the firm facing the idiosyncratic shock and all other firms in the industry which are not directly affected. However, idiosyncratic shocks only matter for *aggregate* outcomes when firms are not atomistic, e.g. as in the setup of Burstein et al. (2020) with a finite number of industries. In contrast, when there is a continuum of industries, as in Atkeson and Burstein (2008), idiosyncratic shocks "wash out" and do not have aggregate effects. Yet, shocks to the distribution of these idiosyncratic shocks still do have aggregate effects, because they change the distribution of sales in all industries. Examples of these asymmetric supply shocks include shocks to the dispersion (e.g. Bloom 2009, Bachmann and Bayer 2014, Ferrari and Queirós 2022) or skewness (e.g. Salgado et al. 2019) of idiosyncratic shocks.

Extensive Margin. Closely related to the simple setup is a class of models with homogeneous active firms and endogenous fluctuations in the number of active firms due to endogenous firm entry and exit (e.g. Jaimovich and Floetotto 2008, Bilbiie et al. 2012, Corhay et al. 2020). In these frameworks, aggregate shocks, e.g. to aggregate productivity, affect firm entry and exit decisions and therefore the number of active firms. Thus, an otherwise perfectly symmetric aggregate shock becomes an asymmetric supply shock due to its propagation via endogenous entry and exit. A similar mechanism is at work in models that feature firms that endogenously choose the number of industries to enter or markets to serve (e.g. Sedláček and Sterk 2017). Symmetric aggregate shocks now affect how many markets any firm serves, and therefore the number of active firms in any market. Again, there is an asymmetric propagation of otherwise symmetric shock.

B.4 Model Simulations

To simulate the model, I draw shocks for all types of shocks with non-zero volatility. Then, having computed firm-level productivity for all firms in all periods, I solve for the industry equilibrium in each industry in each period. Then, I aggregate individual outcomes to aggregate outcomes.

For the calibration, I simulate the model for $T = 30$ periods, to mimic the Compustat data. I treat the model-generated data with exactly the same steps as the actual data.

To compute the aggregate effects, I simulate the model for $T = 5000$ periods.