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Abstract

The rise of market power in the last decades is primarily driven by the largest firms. We propose a theory of these superstar firms in which their technology involves the ability to produce multiple products. Superstars interact with smaller competitors and market share reallocations and product creation generate heterogeneous markup dynamics across firms. Higher market shares of superstars increase the parameter space for macroeconomic indeterminacy. Bayesian estimation of the general equilibrium model suggests the importance of the endogenous amplification of the product creation channel and animal spirits play a non-trivial role in driving U.S. business cycles.

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1 Introduction

Firms are not identical. Many markets are polarized and populated by a few relatively big firms mixed in with a greater number of smaller firms that typically extort less market power. Empirically such dispersion is well documented.[1] In recent decades, this polarization of markets has become more accentuated. Concretely, De Loecker et al. (2020) report not only a steady and significant increase of market power in the U.S. but also that this increase of the average markup was foremost driven by the firms in the top percentiles, the so-called superstar firms.

What are the effects of increasing product market concentration on the workings of the macroeconomy? And what is the role of the competition among big and smaller firms? This paper addresses such questions. It aspires to improve our understanding of superstar firms' effects on macro-outcomes by proposing a tractable framework to study dynamic economies with firm heterogeneity. In particular, the paper provides a theoretical structure that rationalizes the existence of superstars and also allows to examine the influence of superstars on aggregate fluctuations. What is it that makes superstar firms special? In our artificial economy, these firms have access to a technology that results in more market power and larger market shares. Specifically, these technological differences embody Neary's (2010) suggested characteristic of superstars:

> "So far, the advantage of superstar firms has not been specified exactly. One interesting and important case is where the superstar technology involves the ability to produce a large number of products. In that case, the small number of superstar firms are multi-product firms, while the remaining insiders which constitute the competitive fringe are single-product firms. This configuration is consistent with the empirical evidence [...]." [Neary, 2010, p 15]

Along these lines, we propose a model in which firm heterogeneity manifests itself in a group of firms being able to produce multiple products and to gain larger market power relative to mono-product firms. This characterization parallels empirical work by Bernard et al. (2010) who report that a considerable fraction of U.S. manufacturing firms produces in multiple five-digit SIC categories and account for well over 80 percent of total sales. The theoretical framework then allows to shed light on the effects of the superstar firm environment involving changes in market concentration and also of the dispersion of market power. Of particular importance to us is explaining in a unified way the observed market power by a group of large firms, their interactions with ordinary firms and the impact of that environment on aggregate economic behavior. Our theory predicts that superstars charge a higher price, set larger markups and grab a larger market share,

[1] See De Loecker et al. (2020), Kehrig and Vincent (2021), and Edmond et al. (2023).

thus, it provides a story of superstar firms' coexistence and interactions with ordinary firms and it can explain various empirical findings such as in De Loecker et al. (2020). For example, a rising market share of superstar firms is compatible with a greater gap between the markups of large and small firms. We also show how this market structure creates a parameter space for macroeconomic indeterminacy. This indeterminacy implies that profit-seeking businessmen's animal spirits can lead to self-fulfilling macroeconomic outcomes. This indeterminacy mechanism is novel as it comes about from the superstars' endogenously time-varying product creation and operates even when we keep constant the number of firms in the economy.[2] The estimated version of the model using full information Bayesian techniques suggests the endogenous amplification mechanism of product creation within superstar firms is empirically important. Shocks to technology and to the marginal efficiency of investment explain about half of U.S. business cycles and a non-trivial portion of these fluctuations is driven by realized animal spirits, i.e., non-fundamental swings between euphoria and pessimism.

This article comes in five parts. It begins by presenting the baseline model from which we have stripped off various bells and whistles that we insert into the full model when estimating it. This approach allows us to highlight the main mechanisms that drive our results. Section 3 analyses the local dynamics by presenting the parametric zones for indeterminacy. The fourth section presents the Bayesian estimation of the full model. We end the article by listing our conclusions.

2 Model

The economy is populated by two groups of firms. One group consists of smaller mono-product firms. We will coin them ordinary firms. The other firms are superstars: they produce multiple products and, consequently, have more market power. Both groups of firms produce differentiated goods and adjust their markups according to fluctuations in their market shares. The firms' goods are bought by a perfectly competitive sector that welds the varieties together into the final good that is used for consumption purposes or added to the capital stock. People rent out labor and capital services. Firms and households are price takers on factor markets. Time evolves in discrete steps.

2.1 Final goods

Similar to Shimomura and Thisse (2012), final output is a combination of products produced by N ordinary firms and M multi-product superstar firms.[3] M and N are constant

[2] Broda and Weinstein (2010) report that net product creation is procyclical and mostly occurs within firms (rather than via entry and exit). Guo (2023) presents evidence that firms' product scopes are procyclical.

[3] We suppress the time index in these static equations for notational ease.

for now so that we can pinpoint the role of time-varying product scopes as opposed to firm dynamics of entry and exit, which we will introduce later. Final output Y is then

$$Y = \left(\sum_{i=1}^{N} x(i)^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{M} Y(j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

in which $\sigma > 1$ stands for the elasticity of substitution and $x(i)$ is the amount produced by mono-product firm i. Like in Minniti and Turino (2013), since superstar firms are multi-product firms, $Y(j)$ is a composite good

$$Y(j) = \left(\int_0^{S(j)} x(j,s)^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

in which $S(j)$ stands for the product scope and $x(j,s)$ denotes the amount of variety s produced by superstar firm j. The symmetry of the elasticity of substitution σ across these CES bundlers allows to concentrate on the key effects that arise from the market structure. The CES aggregators imply a love of variety $\nu = 1/(\sigma-1)$. The variety effect in (2) provides the benefit of product creation for the superstar firm.[4] If it were zero, superstars would not have any incentive to become multi-product firms. The final profit maximization problem yields two demand functions

$$x(i) = \left(\frac{p(i)}{P} \right)^{-\sigma} Y$$

$$x(j,s) = \left(\frac{p(j,s)}{P} \right)^{-\sigma} Y$$

and the aggregate price index

$$P = \left(\sum_{i=1}^{N} p(i)^{1-\sigma} + \sum_{j=1}^{M} P(j)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

with

$$P(j) = \left(\int_0^{S(j)} p(j,s)^{1-\sigma} ds \right)^{\frac{1}{1-\sigma}}.$$

2.2 Intermediate good firms

Varieties supplied by superstar firms are produced using labor $h(j,s)$ and capital services $\kappa(j,s) \equiv Uk(j,s)$. The variable U stands for the utilization rate set by the owners of physical capital and it is the same for every unit of capital k rented. Firms hire the two

[4] More broadly, the love of variety can be interpreted as a stand-in for other efficiency gains of product creation within multi-product firms (for example, see Pavlov, 2021).

services on perfectly competitive factor markets at the wage rate w and the rental rate of capital services r. Superstar firm j maximizes profits

$$\pi(j) = \int_0^{S(j)} [p(j,s)x(j,s) - wh(j,s) - r\kappa(j,s)]\, ds$$

subject to the production technology

$$\int_0^{S(j)} x(j,s)ds = \int_0^{S(j)} [\kappa(j,s)^{\alpha} h(j,s)^{1-\alpha} - \phi_s]ds - \phi_m, \qquad 0 < \alpha < 1.$$

The variety-level fixed cost ϕ_s restricts the amount of varieties the firm produces. The firm-level fixed cost ϕ_m provides economies of scope and helps to pin down steady state profits. Ordinary firm i only produces a single variety and its production technology is

$$x(i) = \kappa(i)^{\alpha} h(i)^{1-\alpha} - \phi_n$$

in which the fixed cost ϕ_n is calibrated so that it has zero profits at the steady state. Given that both groupings of firms hire on the same factor markets, the first-order conditions are

$$w = (1-\alpha)\Lambda\kappa(j,s)^{\alpha} h(j,s)^{-\alpha} = (1-\alpha)\Lambda\kappa(i)^{\alpha} h(i)^{-\alpha} \tag{3}$$

$$r = \alpha\Lambda\kappa(j,s)^{\alpha-1} h(j,s)^{1-\alpha} = \alpha\Lambda\kappa(i)^{\alpha-1} h(i)^{1-\alpha} \tag{4}$$

in which

$$\Lambda \equiv \alpha^{-\alpha}(1-\alpha)^{\alpha-1} r^{\alpha} w^{1-\alpha} \tag{5}$$

are the marginal costs that are the same for both firm types.

The number of firms in this economy is endogenously determined and, given its superstar character, this number may not be as large to meet the Dixit and Stiglitz (1977) approximation. Thus, we adopt Yang and Heijdra's (1993) suggestion that firms take into account the effect of their prices on the aggregate price index P.[5] Due to each variety having the same production technology, superstar j charges the same price for all of its varieties, i.e., $p(j,s) = p(j,k) = p(j)$. The markups are

$$\mu(j) \equiv \frac{p(j)}{\Lambda} = \frac{\sigma\left(1 - \left(\frac{P(j)}{P}\right)^{1-\sigma}\right)}{\sigma\left(1 - \left(\frac{P(j)}{P}\right)^{1-\sigma}\right) - 1}$$

and

$$\mu(i) \equiv \frac{p(i)}{\Lambda} = \frac{\sigma\left(1 - \left(\frac{p(i)}{P}\right)^{1-\sigma}\right)}{\sigma\left(1 - \left(\frac{p(i)}{P}\right)^{1-\sigma}\right) - 1}$$

[5] Our economy can also be interpreted as a representative sector where firms take into account the effect of their prices on the sectoral price index. We abstract from explicitly modelling sectors to keep the presentation tidy.

in which

$$\left(\frac{P(j)}{P}\right)^{1-\sigma} = \frac{P(j)Y(j)}{PY} \equiv \epsilon(j) \quad \text{and} \quad \left(\frac{p(i)}{P}\right)^{1-\sigma} = \frac{p(i)x(i)}{PY} \equiv \epsilon(i).$$

The markups are thus positively related to the firms' market shares ϵ and for the superstar firm this market share is increasing in the number of varieties $S(j)$ which is endogenously determined via maximizing profits

$$\pi(j) = \left(\frac{p(j) - \Lambda}{p(j)}\right) PY\epsilon(j) - \Lambda[S(j)\phi_s + \phi_m]$$

with respect to $S(j)$. Each superstar takes into account the effect of its product scope on its own prices, prices of all other firms, and the aggregate price index. The first-order condition, $\frac{\partial \pi(j)}{\partial S(j)} = 0$, implies

$$\Lambda\phi_s = \sigma PY \left(\frac{p(j) - \Lambda}{p(j)}\right)^2 \frac{\partial \epsilon(j)}{\partial S(j)} + Y\epsilon(j) \left(\frac{p(j) - \Lambda}{p(j)}\right) \frac{\partial P}{\partial S(j)} \tag{6}$$

where $\frac{\partial \epsilon(j)}{\partial S(j)} > 0$ and $\frac{\partial P}{\partial S(j)} < 0$ (see the Appendix for details). The term on the left-hand side in (6) represents the direct cost of expanding the product scope. The first term on the right-hand side represents the gain to market share due to the love of variety in the CES bundler (2). The second term indicates that profits are reduced due to the higher product scope reducing the aggregate price index. Put differently, the variety effect is required for multi-product firms to exist.

2.3 Symmetric equilibrium

In the symmetric equilibrium each superstar firm produces the same number of varieties $S(j) = S$, charges the same price $p(j) = p_m$, and has the same market share $\epsilon(j) = \epsilon_m$. Similarly, for the ordinary firms $p(i) = p_n$ and $\epsilon(i) = \epsilon_n$ hold. The markups arrange to

$$\mu_m = \frac{\sigma(1 - \epsilon_m)}{\sigma(1 - \epsilon_m) - 1} > \mu_n = \frac{\sigma(1 - \epsilon_n)}{\sigma(1 - \epsilon_n) - 1} > \frac{\sigma}{\sigma - 1} \tag{7}$$

and

$$\epsilon_m = Sp_m^{1-\sigma} > \epsilon_n = p_n^{1-\sigma}$$

with the final good set as the numeraire $P = 1$. Superstar firms have larger market shares and markups than ordinary firms due to the variety effect and the resulting multi-product nature. Since both ordinary and superstar firms hire labor and capital services from the same factor markets and both have constant returns to scale production functions (abstracting from fixed costs), (3) and (4) imply

$$\frac{w}{r} = \frac{1-\alpha}{\alpha}\frac{UK_m}{H_m} = \frac{1-\alpha}{\alpha}\frac{UK_n}{H_n}$$

in which $K_m = MSk_m$, $K_n = Nk_n$, $H_m = MSh_m$ and $H_n = Nh_n$. Therefore, all firms choose identical capital-labor intensities

$$\frac{K_m}{H_m} = \frac{K_n}{H_n}$$

and factor markets are in equilibrium, that is, $K = K_m + K_n$ and $H = H_m + H_n$. From (5) and (7), we can see that superstars charge a higher price than their ordinary counterparts:

$$p_m = \mu_m \alpha^{-\alpha}(1-\alpha)^{\alpha-1} r^\alpha w^{1-\alpha} > p_n.$$

Summing production and demand functions of ordinary firms

$$\sum_{i=0}^{N} x(i) = \sum_{i=0}^{N} \left(\frac{p(i)}{P}\right)^{-\sigma} Y = \sum_{i=0}^{N} \left(\kappa(i)^\alpha h(i)^{1-\alpha} - \phi_n\right)$$

and then applying symmetry yields

$$Y = \frac{p_n}{N\epsilon_n}\left(U^\alpha K_n^\alpha H_n^{1-\alpha} - N\phi_n\right).$$

Similarly, superstar output is

$$\sum_{j=1}^{M} \int_0^{S(j)} x(j,s)ds = \sum_{j=1}^{M} \int_0^{S(j)} \left(\frac{p(j,s)}{P}\right)^{-\sigma} Y ds = \sum_{j=1}^{M} \left(\int_0^{S(j)} \left[\kappa(j,s)^\alpha h(j,s)^{1-\alpha} - \phi_s\right] ds - \phi_m \right)$$

and

$$Y = \frac{p_m}{M\epsilon_m}(U^\alpha K_m^\alpha H_m^{1-\alpha} - MS\phi_s - M\phi_m).$$

Lastly, the first-order condition (6) can be rearranged to define the product scope

$$S = f(\mu_m, \mu_n, N, M, \sigma)\frac{Y}{\phi_s p_m}. \tag{8}$$

It is strongly procyclical and the derivation of the function f can be found in the Appendix.

2.4 Households

Households are personified by a representative agent who chooses sequences of consumption C_t and hours worked H_t to maximize discounted lifetime utility

$$\sum_{t=0}^{\infty} \beta^t \left(\ln C_t - \upsilon \frac{H_t^{1+\chi}}{1+\chi}\right) \qquad \beta > 0, \upsilon > 0, \chi \geq 0$$

in which β is the discount rate, υ denotes the disutility of working and χ is the inverse of the Frisch labor supply elasticity. The agent owns all firms and receives their profits Π_t. The period-budget is constrained by

$$w_t H_t + r_t U_t K_t + \Pi_t \geq I_t + C_t$$

in which I_t is investment that adds to the capital stock

$$K_{t+1} = (1-\delta_t)K_t + I_t$$

and the depreciation rate varies according to

$$\delta_t = \frac{1}{\theta}U_t^{\theta} \qquad \theta > 1.$$

The first-order conditions from the agent's maximization problem comprise of the labor supply

$$\upsilon H_t^{\chi} C_t = w_t$$

the Euler equation

$$\frac{1}{C_t} = \frac{1}{C_{t+1}}\beta\left(r_{t+1}U_{t+1} + 1 - \delta_t\right)$$

and the optimal rate of capital utilization

$$r_t = U_t^{\theta-1}.$$

The steady state versions of these equations then pin down $\theta = \left(1/\beta - 1 + \delta\right)/\delta$.

3 Dynamics and steady state

Let us now analyze the local dynamic properties of the model. The equilibrium conditions are log-linearized around the steady state and the dynamical system is arranged to

$$\begin{bmatrix} \widehat{K}_{t+1} \\ \widehat{C}_{t+1} \end{bmatrix} = \mathbf{J} \begin{bmatrix} \widehat{K}_t \\ \widehat{C}_t \end{bmatrix}.$$

Hatted variables denote percentage deviations from their steady state values and $\mathbf{J}$ is the 2×2 Jacobian matrix of partial derivatives. Consumption C_t is a non-predetermined variable and capital K_t is predetermined. Indeterminacy, and the potential presence of animal spirits, requires both roots of $\mathbf{J}$ to be inside the unit circle.

For given calibrations of markups and σ, the market shares in the steady state are

$$\epsilon_m = 1 - \frac{\mu_m}{\mu_m - 1}\frac{1}{\sigma} > \epsilon_n = 1 - \frac{\mu_n}{\mu_n - 1}\frac{1}{\sigma}.$$

Since these shares sum to unity, $M\epsilon_m + N\epsilon_n = 1$, we can calibrate the market share of superstar firms $M\epsilon_m$ to pin down the number of firms in the steady state

$$N = \frac{1 - M\epsilon_m}{\epsilon_n}$$

and

$$M = \frac{1}{\epsilon_m\left(1 + \frac{N\epsilon_n}{M\epsilon_m}\right)}.$$

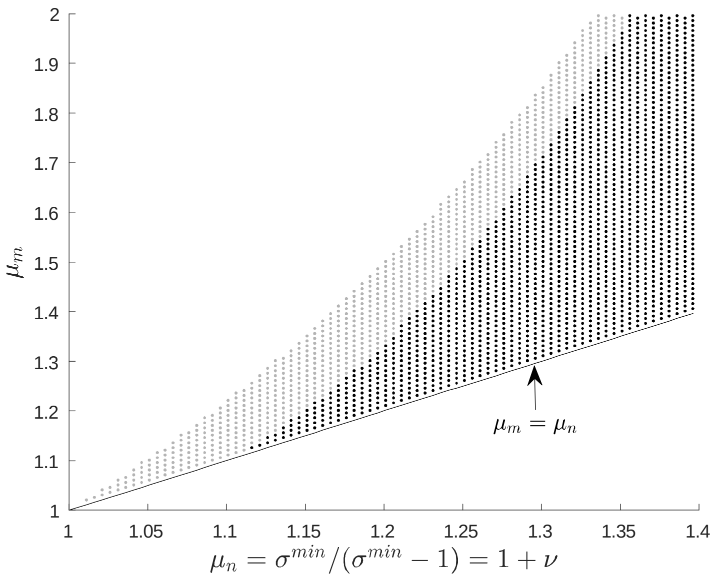

Figure 1: Indeterminacy without entry and exit.

It is then straightforward to show that for each calibration of μ_n, the lower bound on σ is $\sigma^{\min} \equiv \mu_n/(\mu_n - 1)$. As σ approaches this lower bound, the number of ordinary firms approaches infinity and their markups become constant at $\sigma/(\sigma-1)$ as in the monopolistic competition framework. This case is also where the love of variety $\nu = 1/(\sigma - 1)$ hits its maximum. For the upper bound, $\sigma^{\max}$ cannot be greater than either $\mu_n/(\mu_n - 1)(1 + \frac{N\epsilon_n}{M\epsilon_m})$ or $\mu_m/(\mu_m - 1)(1 + \frac{M\epsilon_m}{N\epsilon_n})$ to guarantee $M \geq 1$ and $N \geq 1$.

Figure 1 visualizes the feasible parameter space for the existence of both kind of firms. For easier comparison to previous studies, for example Wen (1998), the standard parameters are calibrated at a quarterly frequency to $\alpha = 0.3$, $\beta = 0.99$, $\delta = 0.025$ and $\chi = 0$. We initially set the market share of superstars at 50 percent. Figure 1 is constructed by setting $\sigma = \sigma^{\min}$, which implies that ordinary firms are monopolistic competitors, i.e., $N \to \infty$ and have constant markups $\mu_n = \frac{\sigma^{\min}}{\sigma^{\min}-1} = 1 + \nu$.[6] Along the graph's lower boundary, the 45 degree line where $\mu_m = \mu_n$, the markups of both sets of firms would be identical. It is also the configuration along which $M \to \infty$ and superstars would become mono-product firms. Off the 45 degree line, however, superstars are multi-product firms, their markups are procyclical and always higher than ordinary firms' markups. The reason is that product creation, both dynamically and in steady state, steals market share from ordinary firms which raises superstars' markups. Finally at the upper boundary, the number of superstars approaches one and the product scope becomes large.

[6] The area of feasible markup combinations in Figure 1 would be unaffected if $\sigma^{\min} < \sigma \leq \sigma^{\max}$, however, ordinary firms' markups would no longer be constant.

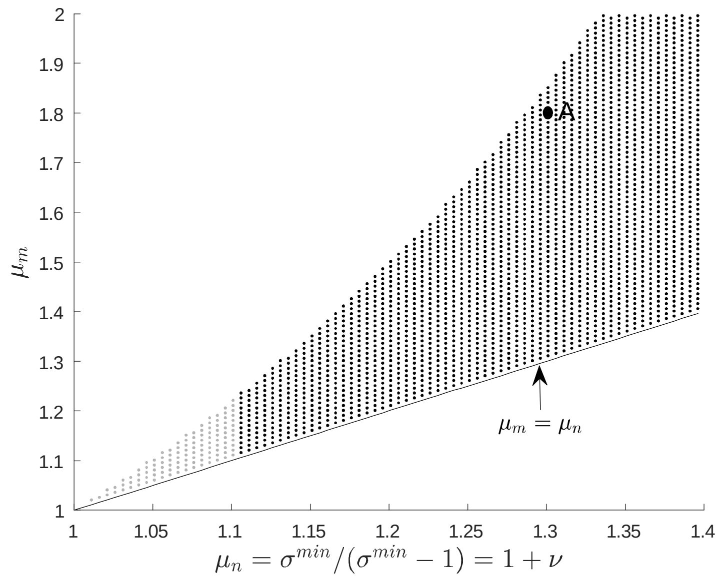

Figure 2: Indeterminacy with entry and exit.

3.1 Indeterminacy mechanism and firm dynamics

Figure 1 also splits the feasible area into indeterminacy and determinacy zones. The darker zone denotes indeterminacy whereas in the lighter shaded area and on the 45 degree line the economy's equilibrium is unique. A necessary condition for indeterminacy is the presence of a certain level of market power, precisely $\mu_m > \mu_n = 1.104$. In other words, without multi-product superstars, this economy would always be determinate. Indeterminacy arises from product creation and the associated variety effect since there is no entry or exit of firms. The indeterminacy is best understood by means of the usual equilibrium wage-hours locus (Farmer and Guo, 1994). Product creation within superstar firms makes this locus upwardly sloping by way of the presence of love of variety in the CES aggregator (2). The composite good from each superstar can be created more efficiently the greater the product scope and variations in product scope generate an endogenous efficiency wedge. Then, if economic sentiments shift into optimistic gear, the labor supply curve shifts up along the upwardly sloping wage-hours locus, thereby validating the animal spirits. Product scope adjustments together with firm heterogeneity thus provide a novel mechanism for indeterminacy and markup dynamics by way of market share reallocations even without entry and exit of firms. As superstars' markups are procyclical, for a given μ_n, raising (steady state) μ_m increases the markup elasticity that may push the economy into its determinacy region in Figure 1. That is, the contractionary effect of the procyclical markup overcomes the efficiency gain from product creation. This outcome disappears once we consider superstars' dynamics in interaction with the entry and exit of ordinary firms.

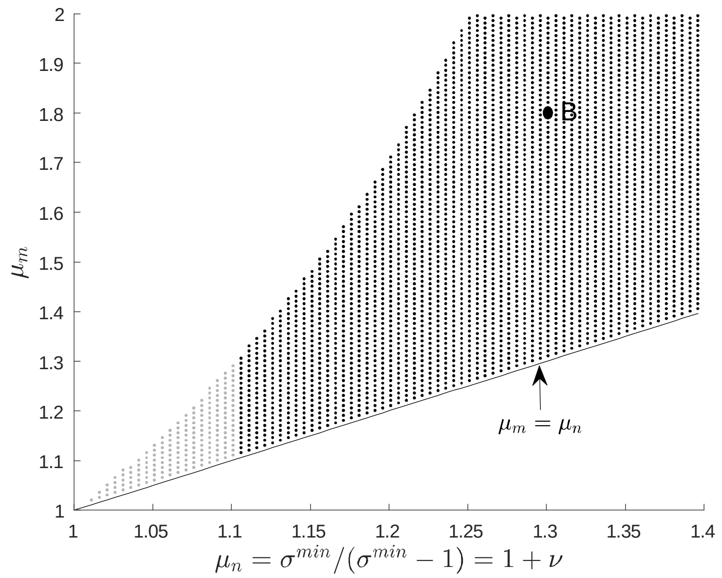

Figure 3: Indeterminacy with higher market share of superstars.

In the next version of the model, the number of ordinary firms N_t is allowed to vary over time and adjusts per free entry that forces their profits to zero.[7] That is, each period firm i's profit is

$$\pi_t(i) = \left(\frac{p_t(i) - \Lambda_t}{p_t(i)}\right) P_t Y_t \epsilon_t(i) - \Lambda_t \phi_n = 0$$

which in symmetric equilibrium boils down to

$$p_{n,t} = (\mu_{n,t} - 1)\frac{\epsilon_{n,t} Y_t}{\phi_n}$$

to determine the number of ordinary firms.[8] Assuming that entry and exit of superstar firms is insignificant at business cycle frequencies, we continue with the assumption of a constant M. Figure 2, in which we again keep σ at $\sigma^{\min}$, displays how entry and exit affects the indeterminacy region.[9] The necessary and sufficient condition for indeterminacy is $\mu_m \geq \mu_n = 1.104$. Indeterminacy not only remains but now exists for a greater range of parameters due to the interaction between entry of ordinary firms and the product scope decisions of superstars. Entry pushes the market shares of both firm types downwards. However, superstar firms are able to defend their market shares by increasing their product scopes. Since higher product scopes and a larger number of ordinary firms both increase efficiency at the hand of the variety effect, the upwardly sloping wage-hours locus becomes steeper.

[7] We now attach the time index to firms' variables.

[8] The entry decision is static to keep the model tractable. Indeterminacy remains when we introduce dynamic entry as in Bilbiie et al. (2012) (see the Appendix).

[9] Again the area of feasible markup combinations would be unaltered if $\sigma^{\min} < \sigma \leq \sigma^{\max}$.

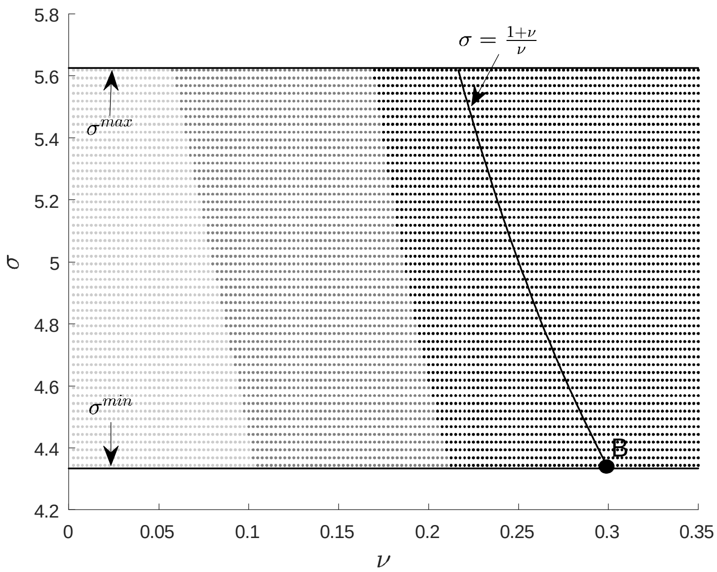

Figure 4: Indeterminacy with separated variety effect.

What is the effect of an increase in the market share of superstars? In Figure 3, $M\epsilon_m$ is now increased to 60 percent from the previous calibration of 50 percent. The indeterminacy zone increases further. If we compare points A and B in Figures 2 and 3, thus keeping the markups constant, the higher market share of superstars supports a higher M while the individual superstar firm has the same product scope.

As emphasized earlier, the love of variety governs the gain to product creation and is the central amplification mechanism for equilibrium indeterminacy. Similar to Pavlov and Weder (2017), we now separate the variety effect ν from the elasticity of substitution σ. Isolating the variety effect allows us to directly set the firms' benefit of product creation without changing the steady state number of firms or their market power. Specifically, the CES bundlers are now

$$Y_t = \left(N_t^{\frac{\nu(\sigma-1)-1}{\sigma}} \sum_{i=1}^{N_t} x_t(i)^{\frac{\sigma-1}{\sigma}} + M^{\frac{\nu(\sigma-1)-1}{\sigma}} \sum_{j=1}^{M} Y_t(j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

and

$$Y_t(j) = \left(S_t(j)^{\frac{\nu(\sigma-1)-1}{\sigma}} \int_0^{S_t(j)} x_t(j,s)^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}}$$

in which $\nu > 0$ denotes the love of variety. Setting $\nu = 1/(\sigma-1)$ brings back the CES aggregators from Section 2. Figure 4 plots parameter zones by varying σ and ν for given steady state markups, $\mu_m = 1.8$ and $\mu_n = 1.3$. Beginning from the right, the indeterminacy zone is partitioned into a darker area in which superstars' markups are procyclical as before and a lighter shaded zone in the middle where they are countercyclical. Superstar markups are always countercyclical in the determinacy zone, the zone furthest to the left. As you can see in Figure 4, indeterminacy requires a certain amount of love for variety as explained earlier. For orientation, at $\nu = 1/(\sigma^{\min} - 1)$ the model is in the same point B as in Figure 3. Beginning in B is a line connecting the combinations at which $\sigma = (1+\nu)/\nu$, i.e., the formulation in (1) and (2). Along the graph's lower boundary $\sigma^{\min}$, ordinary firms are monopolistic competitors with constant markups. For $\sigma^{\min} < \sigma \leq \sigma^{\max}$ ordinary firms' markups are no longer constant but countercyclical. This explains why the boundary between determinacy and indeterminacy is not vertical: if ordinary firms' markups are sufficiently countercyclical, indeterminacy can arise at $\nu = 0.06$ instead of $\nu = 0.104$ at $\sigma^{\min}$. The figure also indicates that procyclical markups of superstars are only possible in the indeterminacy region. Markups of superstar firms become countercyclical for smaller love of variety. This is because a lower variety effect implies a weaker gain to product creation and ability to steal market share from ordinary firms. The entry of ordinary firms then reduces market shares of both firm types. Lastly, through the lens of our model, the finding reported by Burstein et al. (2023), namely that large (French) firms' markups are procyclical, can not arise in the determinacy region of the model.

4 Estimation

This section presents empirical evidence on the importance of the product creation channel and superstars' roles in explaining macroeconomic time series and replicating basic business cycle facts. So far, we have shown that superstar firms can lead to macroeconomic instability. This opens the possibility of animal spirits driving business cycles and we examine their importance in combination with various fundamental shocks. In doing so, we extend our model by exogenous growth, various fundamental aggregate supply and demand shocks as well as external consumption habits. We continue with a separable love of variety and endogenous entry and exit of ordinary firms as described in the previous section.

4.1 Bells and whistles

We add a mix of aggregate supply and demand disturbances to the model. The first such fundamental shock takes the form of labor augmenting technological progress A_t and it affects all firms equally. Aggregate output is now

$$Y_t = \frac{p_{m,t}}{M\epsilon_{m,t}}[(U_t K_{m,t})^\alpha (A_t H_{m,t})^{1-\alpha} - \phi_{s,t} M S_t - \phi_{m,t} M] = \frac{p_{n,t}}{N_t \epsilon_{n,t}}[(U_t K_{n,t})^\alpha (A_t H_{n,t})^{1-\alpha} - N_t \phi_{n,t}]$$

in which we assume all three fixed costs grow at the average rate of technological progress. This technological progress is non-stationary and follows the process

$$\ln A_t = \ln A_{t-1} + \ln a_t$$

with

$$\ln a_t = (1 - \psi_A) \ln a + \psi_A \ln a_{t-1} + \varepsilon_t^A$$

in which $0 \leq \psi_A < 1$ governs the persistence of the shock, $\ln a$ is the average growth rate and ε_t^A is an i.i.d. disturbance with variance σ_A^2. Next, shifts of marginal efficiency of investment z_t affect the transformation of investment to physical capital as in Greenwood et al. (1988)

$$K_{t+1} = (1 - \delta_t) K_t + z_t I_t.$$

The technological shifter follows the exogenous process

$$\ln z_t = (1 - \psi_z) \ln z + \psi_z \ln z_{t-1} + \varepsilon_t^z.$$

As laid out by Justiniano et al. (2011), this shock can be a proxy for capturing disturbances in financial markets. Intuitively, a positive shock to z_t represents a boom in financial markets that reduces borrowing costs for firms, leading to a rise in investment.

The first fundamental demand disturbance is a taste shock Δ_t that increases the marginal utility of consumption as in Christiano (1988). Lifetime utility then becomes

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\Delta_t \ln(C_t - bC_{t-1}) - \upsilon \frac{H_t^{1+\chi}}{1+\chi} \right)$$

in which E_0 denotes the expectations operator and the parameter $0 \leq b < 1$ determines the degree of external consumption habits. The taste shock follows the process

$$\ln \Delta_t = (1 - \psi_\Delta) \ln \Delta + \psi_\Delta \ln \Delta_{t-1} + \varepsilon_t^\Delta.$$

Besides the interpretation of purely changing tastes, this shock could also be interpreted as affecting the economy's labor wedge, i.e., the gap between the marginal rate of substitution between consumption and leisure and the marginal product of labor. Hence, it can be interpreted as a stand-in for other shocks that affect this wedge. The second demand shock is to government expenditures, G_t, financed by lump sum taxes. Consequently, the economy's resource constraint becomes $Y_t = C_t + I_t + G_t$. Government spending follows a stochastic trend

$$A_t^g = (A_{t-1}^g)^{\psi_{ag}} (A_{t-1})^{1-\psi_{ag}}$$

in which ψ_{ag} governs the smoothness of the trend relative to the trend in output. Then, detrended government spending is $g_t \equiv G_t / A_t^g$ and follows

$$\ln g_t = (1 - \psi_g) \ln g + \psi_g \ln g_{t-1} + \varepsilon_t^g.$$

As in Pavlov and Weder (2017), the non-fundamental animal spirits shock is modelled as an expectation error to output that is unrelated to any fundamental changes in the economy[10]. Under indeterminacy, the economy's response to fundamentals is not uniquely determined, and we model the behavior of output as

$$\widehat{Y}_t = E_{t-1}\widehat{Y}_t + \Omega_A \varepsilon_t^A + \Omega_z \varepsilon_t^z + \Omega_\Delta \varepsilon_t^\Delta + \Omega_g \varepsilon_t^g + \varepsilon_t^s \tag{9}$$

in which the parameters Ω_A, Ω_z, Ω_Δ and Ω_g determine the effects of technology, investment, taste and government shocks on output. The term ε_t^s is i.i.d., independent of fundamentals, comes with variance σ_s^2 and it can be thought of as profit-seeking businessmen exercising their animal spirits.

4.2 Bayesian estimation

The model is estimated by way of full-information Bayesian methods using U.S. data with the observables made up of quarterly real per capita growth rates of output, consumption, investment, government spending and the logarithm of per capita hours worked. Justiniano et al. (2011) use credit spread data to identify investment shocks. Similarly, we adopt the spread between BAA corporate bonds and the market yield on 30 year Treasury securities to identify disturbances to the marginal efficiency of investment as in[11]

$$spread_t = \varkappa \widehat{z}_t \qquad \varkappa < 0. \tag{10}$$

We focus on the 1990:I-2019:IV period to coincide with the rise of superstars and to abstract from the COVID-19 pandemic as our small scale model is not designed to deal with its complexities.[12] The Appendix sets out the sources and construction of the data.

We follow Bilbiie et al. (2012) and deflate Y_t, C_t, I_t, and G_t in the model by a data-consistent price index to obtain variables that are better comparable to observed data which does not take into account the welfare improvements of product variety at quarterly frequency. For example, data-consistent output is

$$Y_t^d \equiv \frac{P_t Y_t}{p_t} \equiv \frac{P_t Y_t}{p_{n,t}} N_t \epsilon_{t,n} + \frac{P_t Y_t}{p_{m,t}} M \epsilon_{t,m}$$

which removes the welfare gains that originate from entry and product scope adjust-

[10] Farmer et al. (2015) show that estimation results are robust to the choice of the variable for the expectation error and we confirm this.

[11] Despite having more shocks than observables, we also considered a measurement error in (10) as in Justiniano et al. (2011). The error only explained one percent of the spread. To be in line with Pagan and Robinson (2022), we chose to keep the same number of shocks as observables.

[12] De Loecker et al. (2020) show that the increase in market power of biggest firms largely takes shape post 1990.

ments.[13] Accordingly, the measurement equations are

$$\begin{bmatrix} 100\ln(Y_t/Y_{t-1}) \\ 100\ln(C_t/C_{t-1}) \\ 100\ln(I_t/I_{t-1}) \\ 100\ln(G_t/G_{t-1}) \\ 100\,(\ln H_t/H) \\ spread_t \end{bmatrix} = \begin{bmatrix} \widehat{Y^d}_t - \widehat{Y^d}_{t-1} + \widehat{a}_t \\ \widehat{C^d}_t - \widehat{C^d}_{t-1} + \widehat{a}_t \\ \widehat{I^d}_t - \widehat{I^d}_{t-1} + \widehat{a}_t \\ \widehat{G^d}_t - \widehat{G^d}_{t-1} + \widehat{a^g}_t - \widehat{a^g}_{t-1} + \widehat{a}_t \\ \widehat{H}_t \\ \varkappa\widehat{z}_t \end{bmatrix} + \begin{bmatrix} \overline{a} \\ \overline{a} \\ \overline{a} \\ \overline{a} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{m.e.} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

in which $\overline{a} = 100(a-1)$, $a_t^g = A_t^g/A_t = (a_{t-1}^g)^{\psi_{ag}} a_t^{-1}$, $\varepsilon_t^{m.e.}$ is a measurement error restricted to account for not more than ten percent of output growth and H is the average hours worked over the sample period.

We have six shocks in the model: four fundamental shocks, animal spirits and the measurement error. A common practice estimating models with both determinacy and indeterminacy is to either estimate the model separately under both regimes and then check which specification fits better (Lubik and Schorfheide, 2004) or to estimate the model simultaneously over the entire parameter space (for example, Hirose et al., 2023). However, an issue is that model versions under indeterminacy feature one additional shock, i.e., the animal spirits. This situation implies there are more shocks than observables in the estimations. Pagan and Robinson (2022) show when there is such an excess of shocks, the estimated shock innovations will be correlated which consequently questions the usefulness of variance decompositions. However, a key purpose of our empirical exercise is to assess the relative importance of the model's shocks for driving business cycles. Thus, we refrain from estimating with excess shocks and estimate the model separately under the two parametric zones. For the model's indeterminacy version we have six shocks and the same number of observables. To keep up the situation for the determinacy version, we add an additional fundamental shock to that model version – a transitory technology shock – to avoid stochastic singularity.[14] In the spirit of Lubik and Schorfheide (2004) we can "test for indeterminacy" by comparing the fit of the two specifications in terms of their marginal data densities.

4.2.1 Calibration and priors

We calibrate a subset of the model parameters. We set the quarterly growth rate of labor augmenting technological progress to 0.34 percent to be consistent with the growth rate of per capita real GDP over the sample period and the share of government expenditures G/Y to 0.19. In line with Barkai (2020), we calibrate the share of fixed costs in output so that steady state profits are ten percent. Together with our calibration of $\alpha = 0.3$, this

[13]In line with this, we set the shocks to government expenditures and animal spirits to directly affect the data-consistent variables G_t^d and Y_t^d, respectively.

[14]This setup also provides fairness in the sense of equal number of shocks. Information on the determinate version of the economy is provided in the Appendix.

Table 1: Prior and posterior distributions

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.20	[0.16,0.23]
b	[0,1)	Beta	0.5	0.1	0.48	[0.40,0.57]
ψ_A	[0,1)	Beta	0.5	0.2	0.01	[0.00,0.01]
ψ_z	[0,1)	Beta	0.5	0.2	0.81	[0.75,0.88]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.96	[0.94,0.98]
ψ_g	[0,1)	Beta	0.5	0.2	0.99	[0.98,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.76	[0.58,0.99]
σ_s	R^+	Inverse Gamma	0.1	Inf	0.26	[0.23,0.29]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.68	[0.60,0.75]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.07	[0.04,0.10]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.91	[0.74,1.05]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.81	[0.72,0.89]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
Ω_A	[-3,3]	Uniform	0	1.73	-0.48	[-0.58,-0.38]
Ω_z	[-3,3]	Uniform	0	1.73	1.78	[0.86,2.70]
Ω_Δ	[-3,3]	Uniform	0	1.73	0.35	[0.25,0.45]
Ω_g	[-3,3]	Uniform	0	1.73	0.05	[-0.03,0.13]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-4.90	[-7.13,-2.57]

This table presents the prior and posterior distributions for model parameters and shocks under indeterminacy. Inf implies two degrees of freedom for the inverse gamma distribution. Standard deviations are in percent terms. Log-data density (modified harmonic mean): -775.52.

implies an aggregate labor share of 63 percent which is similar to Elsby et al. (2013). At 56 percent, the labor share of superstars is lower which aligns with Autor et al (2020). We calibrate μ_m, μ_n, σ, and $M\epsilon_m$ as follows. A large portion of firms are multi-product producers. Bernard et al. (2010) report that close to half of U.S. manufacturing firms produce in multiple five-digit SIC categories. These firms account for well over 80 percent of total sales. Accordingly, we cautiously calibrate the market share of superstars to 60 percent, i.e., $M\epsilon_m = 0.6$. A conservative interpretation of the composition of markups reported in De Loecker et al. (2020) suggests a markup of large firms to be around $\mu_m = 1.8$ as this is the rough average for the (revenue weighted) top 75 to top 90 percentiles of firms. Smaller firms, say the top 50 percentile, have seen a steady markup at around $\mu_n = 1.3$. Lastly, we agonistically pick $\sigma = 5$, which falls in the middle of its admissible values. The values of the other standard parameters remain the same as in Section 3. These calibrations form our benchmark and robustness is discussed later.

The remaining parameters are estimated. These include the love of variety, ν, external habits, b, the coefficient mapping the credit spread to investment shocks, $\varkappa$, and parameters that govern the stochastic processes: ψ_A, ψ_z, ψ_Δ, ψ_g, ψ_{ag}, σ_s, σ_A, σ_z, σ_Δ, σ_g, Ω_A, Ω_z, Ω_Δ, Ω_g, and $\sigma^{m.e.}$. Table 1 presents the initial prior and posterior distributions. We employ a normal distribution, truncated at zero, for the variety effect ν. Since this parameter is central to our amplification mechanism which generates indeterminacy, we set the prior to give a prior probability of determinacy of roughly 50 percent. A wide uniform distribution is employed for the expectation error parameters Ω_A, Ω_z, Ω_Δ, Ω_g and the credit spread coefficient $\varkappa$. The shock processes follow the standard inverse gamma distribution.

4.2.2 Estimation results

We estimate the model separately under determinacy and indeterminacy as explained above.[15] The choice of priors leads to a prior predictive probability of indeterminacy of 0.50, thus, indicates no prior bias toward either determinacy or indeterminacy. Our first main result is that, through the lens of our model, the post-1990 period is best characterized by the indeterminate version of our model. Specifically, the log data density is -775.52 under indeterminacy versus -914.59 for its determinate competitor[16]. The central difference between the two economies is that the estimated variety effect is essentially zero in the determinacy model which in turn implies a negligible role of the product creation channel and multi-product firms. Under indeterminacy, the love of variety is non-trivial. In fact, Table 1 shows that it is estimated to be about 0.20. This value, while below Section 2's original CES configuration $1/(\sigma - 1) = 0.25$, indicates a strong amplification mechanism of product creation. Thus, the model's better fit of the data is importantly connected to the product creation channel of superstars in explaining macroeconomic time series and replicating basic business cycle facts.

Table 1 furthermore reports a zero persistence of the permanent technology shock and, consistent with the real business cycle model, a positive shock causes a fall in detrended output at impact. The investment shock is moderately persistent and as expected, raises output. Finally, both demand shocks are highly persistent and also cause an increase in output. The table also shows the estimated shock volatilities including a non-negligible estimate for animal spirits.

Table 2 displays the second moments of the observables, both for actual data and its model counterparts computed at the posterior mean. Our small scale model captures the behavior of U.S. macroeconomic variables reasonably well. The model's second moments are for the most part consistent with the data. The model somewhat overpredicts the volatilities of output and consumption and slightly underpredicts hours worked. One outlier is investment for which the model strongly overpredicts its variance.[17] Correlations with output are well replicated. As a result of its rich internal propagation mechanism, the artificial economy captures data's autocorrelation functions remarkably even without the myriad of real frictions often employed to generate such persistence.

[15] All estimations are done using Dynare (https://www.dynare.org). The posterior distributions are based on 500,000 draws from two separate chains with a 25-30% acceptance rate for each chain.

[16] Results for the determinacy model are delegated to the Appendix.

[17] We ran an alternative estimation using endogenous priors that matches investment data better. It is reported in the Appendix. The key results stay very much robust to these changes.

Table 2: Business cycle dynamics

	Data			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF
$\ln(Y_t/Y_{t-1})$	0.58	1	0.29	0.81	1	0.51
$\ln(C_t/C_{t-1})$	0.47	0.67	0.38	0.62	0.49	0.46
$\ln(I_t/I_{t-1})$	1.66	0.79	0.62	3.13	0.84	0.63
$\ln(G_t/G_{t-1})$	0.77	0.25	0.24	0.85	0.09	0.06
$\ln(H_t/H)$	6.16	0.20	0.99	5.34	0.12	0.99
spread_t	0.60	-0.58	0.85	0.59	-0.26	0.81

Business cycle statistics for the artificial economy are calculated at the posterior mean. σ_x denotes the standard deviation of variable x, $\rho(x, \ln(Y_t/Y_{t-1}))$ is the correlation of variable x and output growth, and ACF is the first order autocorrelation coefficient.

Table 3: Unconditional variance decomposition (in percent)

	$\ln\left(\frac{Y_t}{Y_{t-1}}\right)$	$\ln\left(\frac{C_t}{C_{t-1}}\right)$	$\ln\left(\frac{X_t}{X_{t-1}}\right)$	$\ln\left(\frac{G_t}{G_{t-1}}\right)$	$\ln\left(\frac{H_t}{H}\right)$	$spread_t$
ε_t^s	11.36	0.39	18.00	0.00	2.69	0.00
ε_t^A	28.67	35.43	19.62	8.85	16.34	0.00
ε_t^z	21.50	0.79	32.01	0.00	24.41	100
ε_t^Δ	31.49	63.30	25.03	0.00	46.96	0.00
ε_t^g	2.10	0.09	5.36	91.15	9.60	0.00
$\varepsilon_t^{m.e.}$	4.89	0.00	0.00	0.00	0.00	0.00

Variance decompositions are performed at the posterior mean.

Table 3 displays the forecast error variance decompositions which reveal the relative contribution of each of the six shocks to the macroeconomic aggregates. Shocks to technology and investment explain about half of U.S. business cycle fluctuations. The latter shocks account for a large fraction of investment growth but, overall, investment shocks' importance shrinks considerably when compared to Justiniano et al. (2011). The preference shock explains most of consumption, half of hours worked, and about a third of output and investment. The effect of animal spirits on the business cycle is non-trivial: they drive a modest fraction of output and a sizeable portion of investment. Finally, the government expenditure shock is a negligible source of business cycles. Overall, the relative contributions of supply and demand disturbances to movements in output growth are comparable at around 50 percent each.

4.3 Robustness

How robust are our results? We ran a battery of checks including i) employing the Bianchi and Nicolò (2021) approach of solving and estimating linear rational expectations models under indeterminacy, ii) assuming smaller markups for superstars and ordinary firms, iii) calibrating a lower market share of superstars, and iv) using endogenous priors as in Christiano et al. (2011). All details of these variations to the estimation are delegated to the Appendix. As you will see, the paper's results regarding the estimates, second

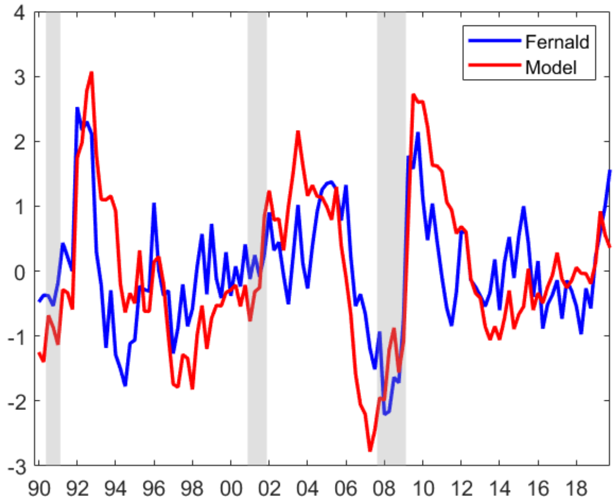

Figure 5: Total factor productivity. Percentage deviations from HP-trend.

moments, and variance decompositions remain very much unchanged.

4.4 External validation

We identify shocks by estimating them in a system and it is thus fair to ask if the estimated shocks are meaningfully labeled. As we estimate the model without employing data on total factor productivity or animal spirits, we now externally validate estimated shocks by comparing them to their empirical counterparts.

For total factor productivity, we consult Fernald's (2014) series in its utilization adjusted form. To make the data comparable, we convert both series into level indices that we then Hodrick-Prescott filter to take out low frequency movements. Figure 5 reports that the estimated series share resemblance with the empirical data and finds a positive correlation at 0.66. This result appears to confirm our interpretation of the shocks.

We also compare the estimated animal spirits with the University of Michigan's sentiment index. We construct a level-index from the smoothed estimates of animal spirits shocks parallel to what we have done for total factor productivity.[18] Figure 6 indicates a mostly positive correlation of the two series at 0.42. To us, this pattern signals that the estimated shocks can be meaningfully coined animal spirits, thus, describing people's extrinsic expectations and how these expectations alternate between euphoric and pessimistic states. This being said, the Michigan sentiment is a composite of extrinsic and intrinsic parts and a less than perfect correlation is expected. Furthermore, the estimated series appears to lead the Michigan index at upper business cycle turning points and both indices begin to fall right before each of the three NBER recessions.

[18] The series are normalized to make them comparable. The Appendix features a parallel figure using

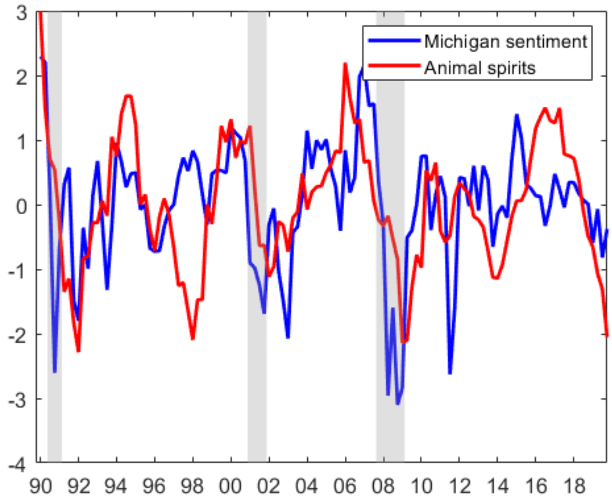

Figure 6: Sentiments and animal spirits. Normalized deviations from HP-trend.

5 Concluding remarks

The rise of market power in the last decades is primarily driven by the largest firms often coined superstars. This paper aspires to improve our understanding of the effect of these firms on aggregate economic behavior. We propose a theory of these superstar firms in which their technology involves the ability to produce multiple products. This ability allows them to charge higher prices, set larger markups and grab a larger market share than ordinary firms. Superstars' product creation and the resulting market share reallocations generate heterogeneous markup dynamics across firms. We plant this market structure into a general equilibrium economy and find higher market shares of superstars increase the parametric space for macroeconomic indeterminacy. This feature allows us to explain the real effects on aggregate fluctuations of extrinsic expectations in combination with fundamental disturbances. A full-information Bayesian estimation of the general equilibrium model reveals the importance of the endogenous amplification of the product creation channel associated with superstars. Through the lens of our theory, the relative contributions of supply and demand disturbances to U.S. aggregate output fluctuations are roughly the same. We find animal spirits play a non-trivial role in driving business cycles.

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A Online appendix

This Appendix contains:

A.1 Data sources and construction

A.2 Derivation of the product scope

A.3 Indeterminacy with dynamic entry and exit of firms

A.4 Determinacy version of the model and estimation results

A.5 Alternative external validation for expectations

A.6 Robustness checks of the Bayesian estimation

A.6.1 Bianchi and Nicolò (2021) method

A.6.2 Alternative markup calibrations

A.6.3 Alternative market share calibrations

A.6.4 Endogenous priors

A.1 Data sources and construction

This Appendix details the source and construction of the U.S. data used in Section 4. All data is quarterly and for the period 1990:I-2019:IV.

1. Gross Domestic Product. Seasonally adjusted at annual rates, billions of chained (2012) dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.6.

2. Gross Domestic Product. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

3. Personal Consumption Expenditures, Nondurable Goods. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

4. Personal Consumption Expenditures, Services. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

5. Personal Consumption Expenditures, Durable Goods. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

6. Gross Private Domestic Investment, Fixed Investment, Residential. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

7. Gross Private Domestic Investment, Fixed Investment, Nonresidential. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

8. Government consumption expenditures and gross investment. Seasonally adjusted at annual rates, billions of dollars. Source: Bureau of Economic Analysis, NIPA Table 1.1.5.

9. Nonfarm Business Hours. Index 2012=100, seasonally adjusted. Source: Bureau of Labor Statistics, Series Id: PRS85006033.

10. Civilian Noninstitutional Population. 16 years and over, thousands. Source: Bureau of Labor Statistics, Series Id: LNU00000000Q.

11. GDP Deflator = (2)/(1).

12. Real Per Capita Output, $Y_t = (1)/(10)$.

13. Real Per Capita Consumption, $C_t = [(3) + (4)]/(11)/(10)$.

14. Real Per Capita Investment, $X_t = [(5) + (6) + (7)]/(11)/(10)$.

15. Real Per Capita Government Expenditures, $G_t = (8)/(11)/(10)$.

16. Per Capita Hours Worked, $H_t = (9)/(10)$.

17. Moody's Seasoned Baa Corporate Bond Yield [DBAA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DBAA.

18. Market Yield on U.S. Treasury Securities at 30-Year Constant Maturity, Quoted on an Investment Basis [DGS30], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS30.

19. Credit spread, (17) − (18).

20. Deviation from average credit spread, $spread_t = (19)-$ average of (19).

21. University of Michigan. Consumer Sentiment [UMCSENT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UMCSENT.

22. Total Factor Productivity. "A Quarterly Utilization-Adjusted Series on Total Factor Productivity", retrieved from https://www.johnfernald.net/TFP.

23. Organization for Economic Co-operation and Development, Business Tendency Surveys (Manufacturing): Confidence Indicators: Composite Indicators: OECD Indicator for United States [BSCICP03USM665S], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BSCICP03USM665S.

A.2 Derivation of the product scope

This Appendix derives the firm's optimal product scope. It largely follows the approach of Minniti and Turino (2013) and Pavlov and Weder (2017). Firm j maximizes profits with respect to $S(j)$ and takes into account the effect of its product scope on its own prices, prices of other firms, and the aggregate price index. First we rewrite profits as

$$\pi(j) = \left(\frac{p(j) - \Lambda}{p(j)}\right) PY\epsilon(j) - \Lambda[S(j)\phi_s + \phi_m]$$

and obtain the first-order condition

$$\frac{\partial \pi(j)}{\partial S(j)} = \sigma P Y \left(\frac{p(j)-\Lambda}{p(j)}\right)^2 \frac{\partial \epsilon(j)}{\partial S(j)} + Y\epsilon(j)\left(\frac{p(j)-\Lambda}{p(j)}\right)\frac{\partial P}{\partial S(j)} - \Lambda\phi_s = 0.$$

Then

$$\frac{\partial \epsilon(j)}{\partial S(j)} = \frac{\epsilon(j)}{S(j)} - (\sigma-1)\epsilon(j)\left[\frac{1}{p(j)}\frac{\partial p(j)}{\partial S(j)} - \frac{1}{P}\frac{\partial P}{\partial S(j)}\right]$$

and for other multi-product firms

$$\frac{\partial \epsilon(k)}{\partial S(j)} = -(\sigma-1)\epsilon(k)\left[\frac{1}{p(k)}\frac{\partial p(k)}{\partial S(j)} - \frac{1}{P}\frac{\partial P}{\partial S(j)}\right]$$

and ordinary firms

$$\frac{\partial \epsilon(i)}{\partial S(j)} = -(\sigma-1)\epsilon(i)\left[\frac{1}{p(i)}\frac{\partial p(i)}{\partial S(j)} - \frac{1}{P}\frac{\partial P}{\partial S(j)}\right].$$

Next, rewrite the aggregate price index as

$$P = \left(\sum_{i=1}^{N} p(i)^{1-\sigma} di + \sum_{k=1}^{M} S(k) p(k)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

From here, we use symmetry to simplify. After some algebra, $\partial P/\partial S(j)$ can be expressed as

$$\frac{\partial P}{\partial S(j)} = N\frac{\epsilon_n}{p_n}\frac{\partial p(i)}{\partial S(j)} + \frac{\epsilon_m}{p_m}\left((M-1)\frac{\partial p(k)}{\partial S(j)} + \frac{\partial p(j)}{\partial S(j)}\right) + \frac{1}{1-\sigma}\frac{\epsilon_m}{S}$$

where

$$\frac{\partial p(i)}{\partial S(j)} = -\sigma(\sigma-1)(\mu_n-1)(1-1/\mu_n)\epsilon_n\left[\frac{\partial p(i)}{\partial S(j)} - p_n\frac{\partial P}{\partial S(j)}\right]$$

$$\frac{\partial p(k)}{\partial S(j)} = -\sigma(\sigma-1)(\mu_m-1)(1-1/\mu_m)\epsilon_m\left[\frac{\partial p(k)}{\partial S(j)} - p_m\frac{\partial P}{\partial S(j)}\right]$$

$$\frac{\partial p(j)}{\partial S(j)} = \sigma(\mu_m-1)(1-1/\mu_m)\left(p_m\frac{\epsilon_m}{S} - (\sigma-1)\epsilon_m\left[\frac{\partial p(j)}{\partial S(j)} - p_m\frac{\partial P}{\partial S(j)}\right]\right).$$

Putting all these together, it can then be shown that $\frac{\partial P}{\partial S(j)} < 0$, $\frac{\partial p(k)}{\partial S(j)} < 0$, $\frac{\partial p(i)}{\partial S(j)} < 0$, $\frac{\partial p(j)}{\partial S(j)} > 0$, $\frac{\partial \epsilon(k)}{\partial S(j)} < 0$, $\frac{\partial \epsilon(i)}{\partial S(j)} < 0$, and $\frac{\partial \epsilon(j)}{\partial S(j)} > 0$. Finally, $\frac{\partial \epsilon(j)}{\partial S(j)}$, $\frac{\partial P}{\partial S(j)}$, and $\frac{\partial p(j)}{\partial S(j)}$ can be substituted in the first-order condition $\frac{\partial \pi(j)}{\partial S(j)} = 0$ to find the product scope

$$S = f(\mu_m, \mu_n, N, M, \sigma)\frac{Y}{\phi_s p_m}$$

where f

$$f = \frac{\frac{\epsilon_m(\mu_m-1)^2\sigma}{\mu_m} - \frac{\epsilon_m^2(\mu_m-1)\left(1+\frac{(\mu_m-1)\sigma(\sigma-1)}{\mu_m\left(1+\frac{\epsilon_m(\mu_m-1)^2\sigma(\sigma-1)}{\mu_m}\right)}\right)}{(\sigma-1)\left[1+\epsilon_m M\left(\frac{\mu_m}{\mu_m+\epsilon_m(\mu_m-1)^2\sigma(\sigma-1)}-1\right)+\epsilon_n N\left(\frac{\mu_n}{\mu_n+\epsilon_n(\mu_n-1)^2\sigma(\sigma-1)}-1\right)\right]}}{\left(1+\frac{\epsilon_m(\mu_m-1)^2\sigma(\sigma-1)}{\mu_m}\right)}$$

and $\epsilon_m = 1 - \frac{\mu_m}{\mu_m-1}\frac{1}{\sigma}$ and $\epsilon_n = 1 - \frac{\mu_n}{\mu_n-1}\frac{1}{\sigma}$.

A.3 Indeterminacy with dynamic entry and exit of firms

This Appendix presents the version of the model where the entry of ordinary firms is dynamic as in Bilbiie et al. (2012) and shows that indeterminacy remains. A prospective entrant i computes its expected value

$$v_t(i) = E_t \sum_{l=1}^{\infty} Q_{t,l}\pi_{n,t+l}(i)$$

where $Q_{t,l}$ is the stochastic discount factor and $\pi_{n,t}(i)$ denotes profits of ordinary firms. There is a time-to-build lag in that period t entrants begin operating in period $t+1$ and the number of firms evolves according to

$$N_t = (1-\delta_n)(N_{t-1} + N_{E,t-1})$$

where δ_n is the exogenous exit probability and $N_{E,t}$ is the number of entrants. Entry occurs until the expected value, $v_t(i)$, is equal to the sunk cost of entry. To enter, f_E amount of labor needs to be hired and since labor is paid the real wage w_t, this sunk cost is equal to

$$v_t(i) = w_t f_E.$$

The production function for new firms is thus

$$N_{E,t} = \frac{H_{E,t}}{f_E}$$

where $H_{E,t}$ is the amount of labor hired for the production of new firms. In a symmetric equilibrium, a representative household enters period t with mutual fund share holdings x_t and has the budget constraint

$$C_t + I_t + v_t(N_t + N_{E,t})x_{t+1} = (\pi_{n,t} + v_t)N_t x_t + w_t H_t + r_t U_t K_t + M\pi_{m,t}$$

where $\pi_{m,t}$ are profits from a constant number of superstar firms and $H_t = H_{E,t} + H_{n,t} + H_{m,t}$. The Euler equation for share holding is then

$$v_t = E_t \beta(1-\delta_n)\frac{C_t}{C_{t+1}}(\pi_{n,t+1} + v_{t+1}).$$

Imposing the equilibrium condition $x_{t+1} = x_t = 1$ for all t gives

$$C_t + I_t + v_t N_{E,t} = \pi_{n,t}N_t + w_t H_t + r_t U_t K_t + M\pi_{m,t} \equiv Y_t$$

where Y_t is GDP consisting of consumption, investment in capital, and investment in new firms. Total investment is then

$$X_t \equiv I_t + v_t N_{E,t}$$

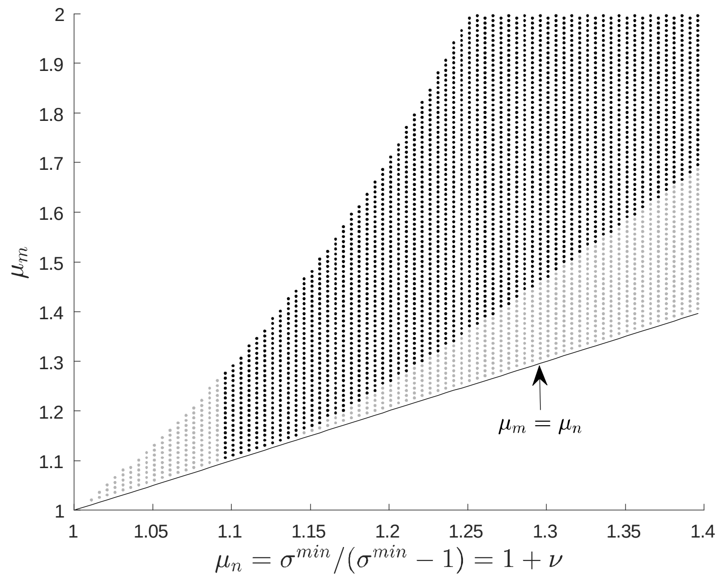

Figure A1: Indeterminacy with dynamic entry.

and the CES aggregator is now

$$Y_{g,t} \equiv C_t + I_t = \left(\sum_{i=1}^{N_t} x_t(i)^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{M} Y_t(j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

Small firms no longer have firm-level fixed costs and the symmetric equilibrium goods production is then

$$Y_{g,t} = \frac{p_{n,t} U_t^{\alpha} K_{n,t}^{\alpha} H_{n,t}^{1-\alpha}}{N_t \epsilon_{n,t}} = \frac{p_{m,t} U_t^{\alpha} K_{m,t}^{\alpha} H_{m,t}^{1-\alpha} - p_{m,t} M S_t \phi_s - p_{m,t} M \phi_m}{M \epsilon_{m,t}}.$$

We calibrate the model as in Section 3 and additionally set $\delta_n = 0.025$ as in Bilbiie et al (2012). Analogous to Figure 3, Figure A1 plots the feasible parameter zones where superstar firms can exist. The indeterminacy region largely remains but the lighter zone on the right side indicates an unstable equilibrium (a source) where markups are not sufficiently different. The lighter zone on the left representing determinacy remains.

A.4 Determinacy version of the model and estimation results

Table A1 presents the prior and posterior distributions of the estimated determinate version of the model. The main difference here is that the animal spirits shock is no longer available and in order to keep the number of shocks equal to observables, we introduce a temporary technology shock, A_t^T, that affects all firms equally with persistence ψ_T and variance σ_T. For example, the output of an ordinary firm is now

$$x_t(i) = A_t^T \kappa_t(i)^\alpha \left[A_t h_t(i)\right]^{1-\alpha} - \phi_{n,t}$$

where

$$\ln A_t^T = (1 - \psi_T) \ln A^T + \psi_T \ln A_{t-1}^T + \varepsilon_t^T.$$

Comparing the log-data densities between Tables 1 and A1, and the posteriors of ν, data clearly favors the indeterminate model with a strong product creation mechanism.

Table A1: Prior and posterior distributions (determinacy model)

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.01	[0.00,0.02]
b	[0,1)	Beta	0.5	0.1	0.40	[0.33,0.47]
ψ_T	[0,1)	Beta	0.5	0.2	0.90	[0.87,0.92]
ψ_A	[0,1)	Beta	0.5	0.2	0.06	[0.04,0.08]
ψ_z	[0,1)	Beta	0.5	0.2	0.96	[0.91,0.99]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.99	[0.98,0.99]
ψ_g	[0,1)	Beta	0.5	0.2	0.98	[0.97,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.99	[0.99,0.99]
σ_T	R^+	Inverse Gamma	0.1	Inf	0.11	[0.09,0.13]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.78	[0.69,0.86]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.03	[0.02,0.04]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.79	[0.69,0.88]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.79	[0.69,0.88]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-13.06	[-17.89,-8.27]

This table presents the prior and posterior distributions for model parameters and shocks of the determinate model. Log-data density (modified harmonic mean): -914.59.

A.5 Alternative external validation for expectations

Figure A2 repeats the external validation of the expectational shocks comparing them to the Business Tendency Surveys (Manufacturing). The plotted data has been constructed as in the main part of the paper. The two series continue to co-move but to a lesser degree.

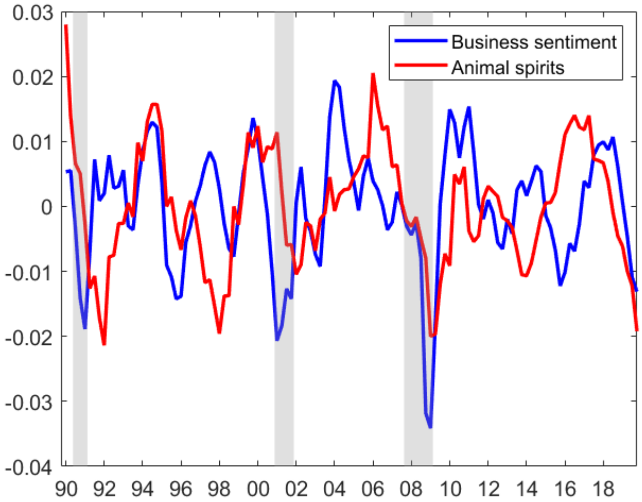

Figure A2: Business Tendency Surveys and animal spirits. Normalized deviations from HP-trend.

A.6 Robustness checks of the Bayesian estimation

A.6.1 Bianchi and Nicolò (2021) method

Bianchi and Nicolò (2021) develop a new method to solve and estimate linear rational expectations (LRE) models under indeterminacy. Their characterization of indeterminate equilibria is equivalent to Lubik and Schorfheide (2003) and Farmer et al. (2015). We closely follow Bianchi and Nicolò (2021) and in the following briefly sketch their methodology while referring the readers to their paper for detailed exposition. Following Bianchi and Nicolò (2021), we append the following autoregressive process to the original LRE model

$$\omega_t = \varphi^* \omega_{t-1} + \varepsilon_t^s - \eta_t$$

in which ε_t^s is the animal spirit shock as before and η_t can be any element of the forecast error vector. As in our baseline analysis, we include the forecast error associated with (data-consistent) output $\eta_t = \widehat{Y}_t^d - E_{t-1}\widehat{Y}_t^d$ without any loss of generality or robustness of the results. The main insight of the Bianchi and Nicolò (2021) approach consists of choosing this auxiliary process in a way that delivers the 'correct' solution. When the original model is indeterminate, the auxiliary process must be explosive so that the augmented representation satisfies the Blanchard-Kahn condition, although it does not for the original model. Accordingly, we set φ^* such that its absolute value is outside the unit circle. As before, we estimate the standard deviation of the animal spirit shock, σ_s. In addition, the animal spirit shock is potentially related to the structural shocks of the model and we capture this association by estimating the correlation between the non-fundamental and fundamental shocks using a uniform prior distribution over the interval $[-1, 1]$. The resulting model is estimated using Bayesian techniques as in the baseline analysis. Table A2 reports the parameter estimates. The parameter estimates turn out to be quite similar to the baseline results, except for the standard deviation of the animal spirit shock which now turns out to be higher than before and the correlations of the animal spirit shock with the fundamental shocks which appear only in the Bianchi-Nicolò method.[19] Nevertheless, as Tables A3 and A4 show, the second moments and forecast error variance decompositions are virtually indistinguishable from our baseline results.

[19] The higher standard deviation of the animal spirit shock is driven by the alternative way of introducing non-fundamental shocks in the estimation under the Bianchi-Nicolò method.

Table A2: Prior and posterior distributions (Bianchi-Nicolò method)

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.20	[0.16,0.23]
b	[0,1)	Beta	0.5	0.1	0.49	[0.41,0.58]
ψ_A	[0,1)	Beta	0.5	0.2	0.00	[0.00,0.01]
ψ_z	[0,1)	Beta	0.5	0.2	0.82	[0.75,0.89]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.96	[0.94,0.98]
ψ_g	[0,1)	Beta	0.5	0.2	0.99	[0.98,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.75	[0.58,1.00]
σ_s	R^+	Inverse Gamma	0.1	Inf	0.53	[0.48,0.58]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.67	[0.60,0.74]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.08	[0.04,0.11]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.90	[0.75,1.06]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.81	[0.72,0.89]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
$\rho_{s,A}$	[-1,1]	Uniform	0	0.58	-0.58	[-0.70,-0.49]
$\rho_{s,z}$	[-1,1]	Uniform	0	0.58	0.22	[0.14,0.32]
$\rho_{s,\Delta}$	[-1,1]	Uniform	0	0.58	0.58	[0.45,0.70]
$\rho_{s,g}$	[-1,1]	Uniform	0	0.58	0.07	[-0.05,0.19]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-4.68	[-6.93,-2.28]

Table A3: Business cycle dynamics (Bianchi-Nicolò method)

	Data			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF
$\ln(Y_t/Y_{t-1})$	0.58	1	0.29	0.82	1	0.51
$\ln(C_t/C_{t-1})$	0.47	0.67	0.38	0.62	0.47	0.47
$\ln(I_t/I_{t-1})$	1.66	0.79	0.62	3.21	0.84	0.63
$\ln(G_t/G_{t-1})$	0.77	0.25	0.24	0.85	0.08	0.06
$\ln(H_t/H)$	6.16	0.20	0.99	5.39	0.13	0.99
spread$_t$	0.60	-0.58	0.85	0.61	-0.26	0.82

Table A4: Unconditional variance decomposition (Bianchi-Nicolò method)

	$\ln\left(\frac{Y_t}{Y_{t-1}}\right)$	$\ln\left(\frac{C_t}{C_{t-1}}\right)$	$\ln\left(\frac{X_t}{X_{t-1}}\right)$	$\ln\left(\frac{G_t}{G_{t-1}}\right)$	$\ln\left(\frac{H_t}{H}\right)$	$spread_t$
ε_t^s	12.35	0.44	19.01	0.00	2.89	0.00
ε_t^A	28.32	34.84	19.05	9.10	15.64	0.00
ε_t^z	22.60	0.87	32.72	0.00	25.83	100
ε_t^Δ	29.86	63.75	23.90	0.00	45.91	0.00
ε_t^g	2.07	0.09	5.32	90.90	9.73	0.00
$\varepsilon_t^{m.e.}$	4.79	0.00	0.00	0.00	0.00	0.00

A.6.2 Alternative markup calibrations

Tables A5-A7 show the estimation results with a lower markup calibration of $\mu_m = 1.5$ and $\mu_n = 1.2$. Once again, we calibrate the elasticity of substitution to the midpoint of its permissible values, this time at $\sigma = 6.8$. All priors remain the same. It can be seen that the estimated parameters, second moments, and variance decompositions change very little relative to our baseline results.

Table A5: Prior and posterior distributions (Alternative markup calibration)

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.21	[0.18,0.24]
b	[0,1)	Beta	0.5	0.1	0.45	[0.37,0.53]
ψ_A	[0,1)	Beta	0.5	0.2	0.00	[0.00,0.01]
ψ_z	[0,1)	Beta	0.5	0.2	0.82	[0.76,0.88]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.97	[0.96,0.99]
ψ_g	[0,1)	Beta	0.5	0.2	0.99	[0.99,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.70	[0.52,0.89]
σ_s	R^+	Inverse Gamma	0.1	Inf	0.24	[0.21,0.27]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.61	[0.55,0.68]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.06	[0.04,0.09]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.79	[0.66,0.92]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.79	[0.70,0.87]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
Ω_A	[-3,3]	Uniform	0	1.73	-0.44	[-0.53,-0.35]
Ω_z	[-3,3]	Uniform	0	1.73	2.05	[1.32,2.99]
Ω_Δ	[-3,3]	Uniform	0	1.73	0.37	[0.27,0.46]
Ω_g	[-3,3]	Uniform	0	1.73	0.02	[-0.04,0.08]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-5.27	[-7.39,-3.11]

Table A6: Business cycle dynamics (Alternative markup calibration)

	Data			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF
$\ln(Y_t/Y_{t-1})$	0.58	1	0.29	0.87	1	0.61
$\ln(C_t/C_{t-1})$	0.47	0.67	0.38	0.58	0.39	0.45
$\ln(I_t/I_{t-1})$	1.66	0.79	0.62	3.56	0.87	0.72
$\ln(G_t/G_{t-1})$	0.77	0.25	0.24	0.83	0.05	0.06
$\ln(H_t/H)$	6.16	0.20	0.99	6.84	0.13	0.99
spread_t	0.60	-0.58	0.85	0.59	-0.25	0.82

Table A7: Unconditional variance decomposition (Alternative markup calibration)

	$\ln\left(\frac{Y_t}{Y_{t-1}}\right)$	$\ln\left(\frac{C_t}{C_{t-1}}\right)$	$\ln\left(\frac{X_t}{X_{t-1}}\right)$	$\ln\left(\frac{G_t}{G_{t-1}}\right)$	$\ln\left(\frac{H_t}{H}\right)$	$spread_t$
ε_t^s	9.48	0.54	13.47	0.00	2.48	0.00
ε_t^A	26.60	37.09	18.73	9.49	14.85	0.00
ε_t^z	25.37	1.50	34.28	0.00	26.44	100
ε_t^Δ	31.30	60.66	26.71	0.00	47.00	0.00
ε_t^g	2.96	0.21	6.81	90.51	9.22	0.00
$\varepsilon_t^{m.e.}$	4.30	0.00	0.00	0.00	0.00	0.00

A.6.3 Alternative market share calibrations

Tables A8-A10 have the same markup calibration from Section 4 but a lower market share of superstars at 50 percent. The midpoint of the permissible values for the elasticity of substitution is now at $\sigma = 4.4$. Again, it can be seen that our results remain robust to this change.

Table A8: Prior and posterior distributions (Lower market share of superstars)

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.20	[0.17,0.22]
b	[0,1)	Beta	0.5	0.1	0.47	[0.39,0.55]
ψ_A	[0,1)	Beta	0.5	0.2	0.00	[0.00,0.01]
ψ_z	[0,1)	Beta	0.5	0.2	0.82	[0.76,0.88]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.97	[0.95,0.99]
ψ_g	[0,1)	Beta	0.5	0.2	0.99	[0.98,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.72	[0.54,0.90]
σ_s	R^+	Inverse Gamma	0.1	Inf	0.24	[0.21,0.27]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.64	[0.57,0.70]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.06	[0.04,0.09]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.84	[0.70,0.98]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.80	[0.71,0.88]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
Ω_A	[-3,3]	Uniform	0	1.73	-0.45	[-0.54,-0.35]
Ω_z	[-3,3]	Uniform	0	1.73	2.00	[1.25,2.97]
Ω_Δ	[-3,3]	Uniform	0	1.73	0.36	[0.26,0.45]
Ω_g	[-3,3]	Uniform	0	1.73	0.04	[-0.03,0.10]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-5.48	[-7.72,-3.01]

Table A9: Business cycle dynamics (Lower market share of superstars)

	Data			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF
$\ln(Y_t/Y_{t-1})$	0.58	1	0.29	0.84	1	0.56
$\ln(C_t/C_{t-1})$	0.47	0.67	0.38	0.60	0.44	0.45
$\ln(I_t/I_{t-1})$	1.66	0.79	0.62	3.34	0.86	0.68
$\ln(G_t/G_{t-1})$	0.77	0.25	0.24	0.84	0.07	0.07
$\ln(H_t/H)$	6.16	0.20	0.99	5.88	0.12	0.99
spread$_t$	0.60	-0.58	0.85	0.60	-0.24	0.82

Table A10: Unconditional variance decomposition (Lower market share of superstars)

	$\ln\left(\frac{Y_t}{Y_{t-1}}\right)$	$\ln\left(\frac{C_t}{C_{t-1}}\right)$	$\ln\left(\frac{X_t}{X_{t-1}}\right)$	$\ln\left(\frac{G_t}{G_{t-1}}\right)$	$\ln\left(\frac{H_t}{H}\right)$	$spread_t$
ε_t^s	10.05	0.46	15.13	0.00	2.36	0.00
ε_t^A	28.47	36.30	19.88	9.53	15.50	0.00
ε_t^z	22.69	1.07	32.47	0.00	23.81	100
ε_t^Δ	31.64	62.03	26.31	0.00	48.39	0.00
ε_t^g	2.55	0.14	6.20	90.47	9.94	0.00
$\varepsilon_t^{m.e.}$	4.60	0.00	0.00	0.00	0.00	0.00

A.6.4 Endogenous priors

Tables A11-A13 show the estimation results under endogenous priors (Christiano et al. 2011). It can be seen that our main results remain robust while the standard deviation of output, government spending, and investment drop to better match U.S. data.

Table A11: Prior and posterior distributions (Endogenous priors)

Prior					Posterior	
Name	Range	Density	Mean	Std. Dev.	Mean	90% Interval
ν	R^+	Normal	0.085	0.05	0.19	[0.16,0.22]
b	[0,1)	Beta	0.5	0.1	0.29	[0.24,0.35]
ψ_A	[0,1)	Beta	0.5	0.2	0.00	[0.00,0.01]
ψ_z	[0,1)	Beta	0.5	0.2	0.93	[0.91,0.95]
ψ_Δ	[0,1)	Beta	0.5	0.2	0.98	[0.97,0.99]
ψ_g	[0,1)	Beta	0.5	0.2	0.99	[0.99,0.99]
ψ_{ag}	[0,1)	Beta	0.5	0.2	0.95	[0.84,0.99]
σ_s	R^+	Inverse Gamma	0.1	Inf	0.23	[0.21,0.26]
σ_A	R^+	Inverse Gamma	0.1	Inf	0.65	[0.59,0.71]
σ_z	R^+	Inverse Gamma	0.1	Inf	0.09	[0.05,0.12]
σ_Δ	R^+	Inverse Gamma	0.1	Inf	0.70	[0.63,0.77]
σ_g	R^+	Inverse Gamma	0.1	Inf	0.75	[0.70,0.81]
$\sigma^{m.e.}$	$[0, 0.18]$	Uniform	0.09	0.05	0.18	[0.18,0.18]
Ω_A	[-3,3]	Uniform	0	1.73	-0.44	[-0.52,-0.37]
Ω_z	[-3,3]	Uniform	0	1.73	0.97	[0.43,1.52]
Ω_Δ	[-3,3]	Uniform	0	1.73	0.57	[0.50,0.64]
Ω_g	[-3,3]	Uniform	0	1.73	0.13	[0.07,0.18]
$\varkappa$	[-20,0]	Uniform	-10	5.77	-4.04	[-5.92,-1.99]

Table A12: Business cycle dynamics (Endogenous priors)

	Data			Model		
x	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF	σ_x	$\rho(x, \ln(Y_t/Y_{t-1}))$	ACF
$\ln(Y_t/Y_{t-1})$	0.58	1	0.29	0.75	1	0.34
$\ln(C_t/C_{t-1})$	0.47	0.67	0.38	0.65	0.68	0.30
$\ln(I_t/I_{t-1})$	1.66	0.79	0.62	2.39	0.81	0.56
$\ln(G_t/G_{t-1})$	0.77	0.25	0.24	0.76	0.14	0.02
$\ln(H_t/H)$	6.16	0.20	0.99	4.71	0.10	0.99
spread$_t$	0.60	-0.58	0.85	0.98	-0.09	0.93

Table A13: Unconditional variance decomposition (Endogenous priors)

	$\ln\left(\frac{Y_t}{Y_{t-1}}\right)$	$\ln\left(\frac{C_t}{C_{t-1}}\right)$	$\ln\left(\frac{X_t}{X_{t-1}}\right)$	$\ln\left(\frac{G_t}{G_{t-1}}\right)$	$\ln\left(\frac{H_t}{H}\right)$	$spread_t$
ε_t^s	10.92	0.20	24.91	0.00	2.81	0.00
ε_t^A	29.54	44.45	17.61	1.91	9.54	0.00
ε_t^z	12.46	0.38	26.57	0.00	19.59	100
ε_t^Δ	38.33	54.91	27.00	0.00	56.16	0.00
ε_t^g	3.08	0.07	3.91	98.09	11.90	0.00
$\varepsilon_t^{m.e.}$	5.67	0.00	0.00	0.00	0.00	0.00