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ENDOGENOUS FIRM ENTRY IN AN ESTIMATED MODEL OF THE U.S. BUSINESS CYCLE

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A recent theoretical literature highlights the role of endogenous firm entry as an internal amplification mechanism of business cycle fluctuations. The amplification mechanism works through the competition effect (CE) and the variety effect (VE). This paper tests the significance of this amplification mechanism, quantifies its importance, and disentangles the CE and VE. To this end, we estimate a medium-scale real business cycle model with firm entry for the U.S. economy. The CE and VE are estimated to be statistically significant. Together, they amplify the volatility of output by 8.5% relative to a model in which both effects are switched off. The CE accounts for most amplification, whereas the VE only plays a minor role.

Keywords: Competition Effect, Entry, Mark-Ups, Variety Effect

1. INTRODUCTION

Standard dynamic stochastic general equilibrium (DSGE) models used for forecasting and policy analysis have a fixed range of products and firms and neglect the effect of firm entry on business cycle fluctuations.[1] Empirical evidence on firm and product entry, however, suggests otherwise. First, the number of firms varies substantially over the business cycle and is strongly procyclical. Second, the opening of establishments explains around 20% of quarterly job gains. Third, product creation (at new and existing firms) accounts for almost 50% of output in a 5 year interval.[2]

In light of these findings, a recent theoretical branch of the literature has started to study the role of endogenous firm (or product) entry in business cycle

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fluctuations.[3] This literature identifies endogenous entry as an important amplification mechanism for business cycle fluctuations.

The amplification mechanism for output fluctuations works through the variety effect (VE) and the competition effect (CE). The VE describes the productivity gains from additional varieties. The CE captures the inverse relation between the number of producers and price mark-ups. To understand how these effects amplify output fluctuations, consider a model economy where an endogenous number of monopolistically competitive firms produce intermediate goods that are used to produce a final good. Entry takes place in the intermediate goods sector. Now suppose that an expansionary shock (a shock that raises output) induces new firms to enter the market. In the presence of the VE, there are increasing returns to specialization: An increase in the number of firms—equivalent to an increase in the number of intermediate goods—raises the productivity of any of the intermediate goods used in the production of the final good. Due to this productivity gain, output will increase by more than if there were no VE.[4] In the presence of the CE, the rise in the number of firms erodes market power in the intermediate goods sector. Price mark-ups fall which in turn boosts aggregate demand. As a consequence, output will increase by more than under constant price mark-ups.

This paper aims to test the significance of this amplification mechanism, to quantify its importance, and to disentangle the CE and the VE in a medium-scale business cycle model. To this end, we use the firm entry model by Bilbiie et al. (2012), extend it with several real frictions, and estimate the model on U.S. data with Bayesian methods. We investigate the capacity of the model in fitting the data, study how firm entry affects the estimates of structural model parameters, and explore the amplification mechanism embedded in the firm entry model for transitory supply and demand shocks.

The model is characterized by sunk entry costs and a translog final goods production technology as proposed by Feenstra (2003).[5] The number of firms is endogenously determined by a free entry condition that equates expected future profits with entry costs. Under the translog technology, both the CE and the VE are present. The CE is demand-side-driven and stems from the fact that the substitutability between different varieties, and hence the price elasticity of demand, is increasing in the number of varieties.

We find the CE and VE to be statistically significant. To quantify the strength of the amplification mechanism on output fluctuations and to disentangle the CE and VE, we specify two counterfactual model frameworks with a constant elasticity of substitution (CES) production technology, where either the CE or both effects are switched off. We measure the amplification as the percentage volatility difference in gross domestic product (GDP), consumption, and investment across the three model variants. By conducting counterfactual simulations, we find that the CE and VE substantially amplify fluctuations in output and consumption, but dampen fluctuations in investment. For output, the total increase in volatility is given by 8.5%. The CE accounts for most of the amplification, amplifying output by 7%, whereas the increase through the VE only amounts to 1.5%.

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The way firm entry affects output fluctuations is shock dependent. The conditional cyclicality of the number of firms determines whether firm entry, through the CE and VE, amplifies or dampens output fluctuations. Shocks to labor productivity and to wage mark-ups lead to procyclical movements in the number of firms that amplify output responses (through countercyclical movements in price mark-ups and procyclical movements in factor productivity) in comparison to an economy where the CE and VE are absent. In contrast, the CE and VE dampen the output effects of investment-specific technology and aggregate demand shocks, for which the conditional correlation between the number of firms and output is negative. This is because a decline in the number of firms, by raising price mark-ups and lowering factor productivity, dampens the expansionary output effects after favorable shocks to investment-specific technology and to aggregate demand.

The evidence on the cyclicality of mark-ups does not speak with a single voice. A large body of literature finds evidence for countercyclical mark-ups, for example, Bils (1987), Rotemberg and Woodford (1999), and Mazumder (2014), whereas there is competing evidence of procyclicality, see Nekarda and Ramey (2013). Countercyclical responses of mark-ups to technology shocks and monetary policy shocks have recently been documented by Etro and Colcagio (2010) and Lewis and Poilly (2012). However, mark-ups are not directly observable. The literature uses relations from structural models to construct a measure of mark-ups from observable variables. In our framework, a fully model-consistent construction of a mark-up series is not possible. We therefore exclude a mark-up series from our baseline estimation and treat the mark-up as an unobserved state in our estimation procedure.[6] The implied cyclicality of price mark-ups, using our estimates, is shock dependent. Productivity and wage mark-up shocks entail a countercyclical response of mark-ups. In response to shocks to aggregate demand and to investment-specific technology, mark-ups behave procyclical.

This article is among the first attempts to bring a business cycle model with firm entry to the data. Lewis and Poilly (2012) study the role of firm entry for the monetary transmission mechanism by minimizing the distance between the impulse responses to a monetary policy shock generated by a sticky-price entry model and those obtained from a VAR. A complementary work to ours is Lewis and Stevens (2015). They estimate—as we do—a business cycle model with firm entry using Bayesian methods and provide evidence on the parameter governing the CE. However, the papers differ in modeling details and pursue different research questions. In particular, we assess how endogenous firm entry, through the CE and VE, amplifies fluctuations in *output* (and its components) that is absent in the study of Lewis and Stevens (2015). In contrast, they analyze how firm entry, via the CE, alters inflations dynamics.[7]

Closely related to our paper is the work of Jaimovich and Floetotto (2008). Based on a calibrated and—apart from firm entry—standard real business cycle model, they show that the amplification effect associated with firm entry amplifies the impacts of technology shocks on output by 64–158%, depending on the exact specification of their model. This paper confirms the qualitative results in

Jaimovich and Floetotto (2008) but finds the quantitative impact of firm entry to be less dominant. Our paper extends their work in a number of ways. First, we carry out a full-fledged estimation of a medium-scale real business cycle model that already accounts for a large fraction of economic fluctuations. This approach enables us to extract the net amplification effect associated with firm entry. Moreover, we provide an estimate of the strength of the amplification mechanism. Second, we consider several shocks and demonstrate that the role of firm entry in aggregate fluctuations depends on the nature of the shock. Third, in the model of Jaimovich and Floetotto (2008), the VE is turned off, and the sole focus lies on the CE. The latter is supply-side-driven and stems from the strategic interaction between oligopolistic firms.[8] However, Lewis and Poilly (2012) find that a model with strategic interactions cannot generate an empirically relevant CE. Therefore, we consider a demand-side-driven CE based on a translog production technology.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 shows analytically the effects that the CE and VE have on the model's dynamics. Section 4 describes the data and the estimation procedure. Section 5 discusses the estimation results. Section 6 analyzes how the CE and VE influence business cycle dynamics in the estimated model and quantifies the amplification mechanism. Section 7 tests the robustness of our results. Section 8 concludes.

2. THE MODEL

This section outlines our business cycle model for the U.S. economy. The core is a medium-scale real business cycle model that is characterized by monopolistic competition on product and labor markets, habit formation in consumption, investment adjustment costs, variable capital utilization, and non-separable preferences as proposed by Jaimovich and Rebelo (2009).[9] To this, we add the entry model proposed by Bilbiie et al. (2012) that features a VE and a demand-side-driven CE stemming from a translog production technology of final goods producers.

The model economy consists of a government, a fixed mass of final goods producers, labor bundlers, households, and a time-varying and endogenously determined mass of intermediate goods producers. Households consume, invest in physical capital and in start-ups (or new firms), hold government bonds and equity of intermediate goods producers, and supply differentiated labor types to a labor bundler under monopolistically competitive conditions. Competitive labor bundlers aggregate the differentiated labor types into a homogeneous labor input. A time-varying mass of monopolistic firms employ labor and capital to produce differentiated intermediate goods. The creation of a new product variety—equivalent to the establishment of a new firm—requires labor input. The entry of firms into the intermediate goods market is endogenously determined by a free entry condition that equates expected future profits with entry costs. Final goods producers bundle the intermediate goods to a homogenous final good used for private and government consumption and for investment in physical capital. We specify a translog production function as in Feenstra (2003) to describe how intermediate goods are combined to produce final goods. This specification gives rise to countercyclical price mark-ups and increasing returns to specialization (or love of variety). In the following, we discuss the model in more detail.

2.1. Final Goods Producers

There is a mass N_t of monopolistically competitive firms, each producing a different variety of an intermediate good, indexed by $i \in [0, N_t]$. Final goods producers buy the differentiated intermediate goods or varieties $y_{i,t}$ at a price $p_{i,t}$, bundle them to a homogenous final good Y_t^C, and sell it to the households and to the government under perfectly competitive conditions at a price P_t. A final goods producer maximizes its profits $Y_t^C P_t - \int_0^{N_t} p_{i,t} y_{i,t} di$ subject to a final goods production function that is specified using the translog cost function as proposed by Feenstra (2003). The first-order condition for profit maximization yields the demand function for variety i, given by $y_{i,t} = \frac{\partial P_t}{\partial p_{i,t}} Y_t^C$.

In a symmetric equilibrium, all firms make identical choices: $y_{i,t} = y_t$, $p_{i,t} = p_t$, and $\rho_{i,t} = \rho_t$, where $\rho_{i,t} \equiv p_{i,t}/P_t$ is the relative price of variety i. The demand function for a single variety is then given by $y_t = (\rho_t N_t)^{-1} Y_t^C$ and the price index can be written as $P_t = \exp[(\tilde{N} - N_t)/(2\tilde{\sigma}\tilde{N} N_t)] p_t$, where $\tilde{N}$ is the mass of potential entrants. The price elasticity of demand (or elasticity of substitution between different varieties), ε_t, is increasing in the number of varieties: $\varepsilon_t = 1 + \tilde{\sigma} N_t$ with $\tilde{\sigma} > 0$.[10] The degree of increasing returns to specialization (the VE) is captured by the elasticity of the relative price with respect to the number of firms, which is given by $\omega_t = \frac{\partial \rho_t}{\partial N_t} \frac{N_t}{\rho_t} = (2\tilde{\sigma} N_t)^{-1}$.

2.2. Intermediate Goods Producers

Each intermediate good is produced by a monopolist $i \in [0, N_t]$ that uses the amount $l_{i,t}$ of labor, the amount $k_{i,t}^s$ of capital services, and the constant returns to scale technology

$$y_{i,t} = (z_t l_{i,t})^{\alpha} (k_{i,t}^s)^{1-\alpha} \tag{1}$$

to produce its output $y_{i,t}$. z_t is a labor productivity shifter, which follows the exogenous AR(1) process $\log z_t = (1 - \rho_z) \log z + \rho_z \log z_{t-1} + \varepsilon_t^z$, where z is the steady state of z_t, and ε_t^z is i.i.d.$N(0, \sigma_{\varepsilon^z}^2)$. $\alpha \in (0, 1)$ denotes the share of labor in production. The firm takes the real factor prices w_t and r_t^k as given. Firm i chooses prices $p_{i,t}$ and factor inputs to maximize real profits $d_{i,t} = \frac{p_{i,t}}{P_t} y_{i,t} - w_t l_{i,t} - r_t^k k_{i,t}^s$ subject to the production technology and the demand for its variety.

At the optimum, the firm sets its real price as a mark-up, μ_t^p, over real marginal costs, mc_t:

$$\frac{p_{i,t}}{P_t} = \mu_t^p mc_t\,, \tag{2}$$

where $\mu_t^p = \frac{\varepsilon_t}{\varepsilon_t - 1}$. Inserting $\varepsilon_t = 1 + \tilde{\sigma} N_t$ yields $\mu_t^p = 1 + \frac{1}{\tilde{\sigma} N_t}$, implying that the mark-up is decreasing in the number of goods. The CE is captured by the (negative) elasticity of the mark-up with respect to the number of goods (or firms), which is given by $\xi_t = -\frac{\partial \mu_t^p}{\partial N_t} \frac{N_t}{\mu_t^p} = (1 + \tilde{\sigma} N_t)^{-1}$.

The demands of firm i for hours and capital are given by

$$w_t = \alpha mc_t \frac{y_{i,t}}{l_{i,t}} , \tag{3}$$

$$r_t^k = (1-\alpha) mc_t \frac{y_{i,t}}{k_{i,t}^s} . \tag{4}$$

In a symmetric equilibrium, the aggregate production of intermediated goods is given by $N_t y_t = (z_t L_t^C)^\alpha (K_t^s)^{1-\alpha}$, where $L_t^C = N_t l_t$ and $K_t^s = N_t k_t^s$. Total profits can be expressed as $N_t d_t = (1 - 1/\mu_t^p) Y_t^C$.

2.3. Labor Bundlers

The economy is made up by a continuum of households, indexed by $j \in [0, 1]$. Each household is a monopolistic supplier of a differentiated labor type $L_{j,t}$. Analogously to final goods producers, labor bundlers combine the differentiated labor types to a homogenous labor input L_t, according to $L_t = (\int_0^1 L_{j,t}^{1/\mu_t^w} dj)^{\mu_t^w}$. The wage mark-up μ_t^w is assumed to follow the ARMA(1,1) process $\log \mu_t^w = (1-\rho_\mu) \log \mu^w + \rho_\mu \log \mu_{t-1}^w + \varepsilon_t^\mu + \nu \varepsilon_{t-1}^\mu$, where μ^w is the steady state of μ_t^w, and ε_t^μ is i.i.d.$N(0, \sigma_{\varepsilon^\mu}^2)$.[11] Profit maximization by the perfectly competitive labor bundlers yields the labor demand function:

$$L_{j,t} = \left(\frac{w_{j,t}}{w_t} \right)^{-\mu_t^w/(\mu_t^w - 1)} L_t , \tag{5}$$

where $w_t = (\int_0^1 w_{j,t}^{-1/(\mu_t^w - 1)} dj)^{-(\mu_t^w - 1)}$ is the real wage paid for the homogenous labor input, and $w_{j,t}$ is the (real) price of labor type j.

2.4. Households

Each household j maximizes the following lifetime utility function proposed by Jaimovich and Rebelo (2009):

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \chi_t \log \left(C_{j,t} - bC_{j,t-1} - \psi L_{j,t}^\eta S_{j,t} \right) , \tag{6}$$

where $C_{j,t}$ and $L_{j,t}$ denote consumption and hours worked, respectively. $\beta \in (0, 1)$ is the discount factor, $\psi > 0$ is a scale parameter, and $b \in [0, 1)$ measures the degree of (internal) habit formation. $\chi_t > 0$ is a preference shock and follows $\log \chi_t = \log \chi + \varepsilon_t^\chi$, where χ is the steady state of χ_t, and ε_t^χ is i.i.d.$N(0, \sigma_{\varepsilon^\chi}^2)$.

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S_t is a habit-adjusted weighted average of current and past consumption, which evolves over time according to

$$S_{j,t} = (C_{j,t} - bC_{j,t-1})^{\gamma} S_{j,t-1}^{1-\gamma}, \tag{7}$$

where $\gamma \in (0, 1]$ governs the wealth elasticity of labor supply, and $\theta = \eta - 1$ is the Frisch elasticity of labor supply in the limiting case $\gamma = b = 0$.

The household's period-by-period budget constraint (in units of final goods) is given by

$$\begin{aligned} C_{j,t} + I_{j,t} + \frac{B_{j,t}}{R_t} + v_t x_{j,t} + \frac{f_{E,t}}{z_t} w_t N_{E,j,t} + T_t &= w_{j,t} L_{j,t} + r_t^k K_t^s \\ &+ B_{j,t-1} + (1-\delta)(v_t + d_t) \\ &\times \left\{ x_{j,t-1} + \left[1 - \frac{\kappa_E}{2} \left(\frac{N_{E,j,t-1}}{N_{E,j,t-2}} - 1 \right)^2 \right] N_{E,j,t-1} \right\}. \end{aligned} \tag{8}$$

The household purchases the amount $C_{j,t}$ of final goods, pays lump-sum taxes T_t, buys risk-less government bonds $B_{j,t}$ at a price $1/R_t$, and buys equity of firms operating in the intermediate goods market $x_{j,t}$ at a price v_t. Each bond pays one unit of the final good one period later. Each unit of equity bought at period $t-1$ pays a (real) profit equal to $(1-\delta)d_t$ and is worth $(1-\delta)v_t$, where $\delta \in (0, 1)$ denotes the exogenous exit rate of firms.

The household invests into new firms $N_{E,j,t}$. Setting up a new firm (or inventing a new product) requires $f_{E,t}/z_t$ units of the composite labor input, where $f_{E,t}$ represents an entry cost shock that follows the exogenous AR(1) process $\log f_{E,t} = (1-\rho_{f_E}) \log f_E + \rho_{f_E} \log f_{E,t-1} + \varepsilon_t^{f_E}$, where f_E is the steady state of $f_{E,t}$, and $\varepsilon_t^{f_E}$ is i.i.d.$N(0, \sigma^2_{\varepsilon f_E})$. Consequently, household j spends $f_{E,t}/z_t \cdot w_t N_{E,j,t}$ on investment in new firms. We assume that it takes one period before newly established firms become operational.[12] During this period, new firms are hit by the exogenous exit shock δ. In addition, we follow Lewis (2009) and model an endogenous failure rate that is an increasing function of the change in firm entry. The payoff in period t from investing in new firms in period $t-1$ is thus given by $(1-\delta)(v_t + d_t)[1 - \frac{\kappa_E}{2}(\frac{N_{E,j,t-1}}{N_{E,j,t-2}} - 1)^2] N_{E,j,t-1}$. The parameter κ_E serves as the counterpart of the investment adjustment cost parameter κ_I, introduced below, at the firm entry margin.

Finally, the household invests the amount $I_{j,t}$ into physical capital $K_{j,t}$, which is assumed to be owned by households. Capital evolves according to the following law of motion:

$$K_{j,t} = [1 - \delta^K(u_{j,t})] K_{j,t-1} + u_t^I \left[1 - \frac{\kappa_I}{2} \left(\frac{I_{j,t}}{I_{j,t-1}} - 1 \right)^2 \right] I_{j,t}, \tag{9}$$

where $\frac{\kappa_I}{2}(I_{j,t}/I_{j,t-1}-1)^2$ represents investment adjustment costs, and $u_t^I > 0$ is an investment-specific technology shock that follows the exogenous AR(1) process $\log u_t^I = (1-\rho_I)\log u^I + \rho_I \log u_{t-1}^I + \varepsilon_t^I$, where u^I is the steady state of u_t^I, and ε_t^I is i.i.d.$N(0, \sigma_{\varepsilon^I}^2)$. The household chooses the capital utilization rate $u_{j,t}$, which transforms physical capital into capital services $K_{j,t}^s$ according to $K_{j,t}^s = u_{j,t}K_{j,t-1}$. We assume that an increasing utilization of capital implies a higher depreciation rate $\delta^K(u_{j,t})$, specified as

$$\delta^K(u_{j,t}) = \delta_0 + \delta_1(u_{j,t}-1) + \frac{\delta_2}{2}(u_{j,t}-1)^2\,, \tag{10}$$

where δ_0 is the capital deprecation rate in a deterministic steady state in which capital utilization is set to unity. The elasticity of capital utilization with respect to the rental rate of capital is given by δ_1/δ_2. Capital services $K_{j,t}^s$ are rented to intermediate goods firms at a rental rate r_t^k.

Household j chooses $\{C_{j,t}, w_{j,t}, S_{j,t}, I_{j,t}, N_{E,j,t}, u_{j,t}, K_{j,t}, x_{j,t}, B_{j,t}\}_{t=0}^{\infty}$ taking as given $\{w_t, r_t^k, R_t, v_t, d_t, L_t, T_t, z_t, f_{E,t}, u_t^I, \chi_t, \mu_t^w\}_{t=0}^{\infty}$ and the initial conditions $B_{-1}, K_{-1}, C_{-1}, I_{-1}, N_{E-1}, S_{-1}$ so as to maximize (6) subject to (7)–(10) and (5). Since all households will choose in equilibrium the same wage and quantities, we can now assume symmetry and drop the index j. Let λ_t^C, $\lambda_t^C Q_t$, and λ_t^S denote Lagrange multipliers for the budget constraint, the capital accumulation equation, and the definition of S_t, respectively. The first-order conditions read as follows:

$$\lambda_t^C = \beta R_t \,\mathrm{E}_t\left(\lambda_{t+1}^C\right)\,, \tag{11}$$

$$\lambda_t^C Q_t = \beta\,\mathrm{E}_t\left(\lambda_{t+1}^C\left\{r_{t+1}^K u_{t+1} + Q_{t+1}[1-\delta^K(u_{t+1})]\right\}\right)\,, \tag{12}$$

$$\lambda_t^C v_t = (1-\delta)\beta\,\mathrm{E}_t\left[\lambda_{t+1}^C\left(v_{t+1}+d_{t+1}\right)\right]\,, \tag{13}$$

$$\lambda_t^C = \left(\chi_t V_t - \gamma\lambda_t^S\frac{S_t}{C_t - bC_{t-1}}\right) - \beta b\,\mathrm{E}_t\left(\chi_{t+1}V_{t+1} - \gamma\lambda_{t+1}^S\frac{S_{t+1}}{C_{t+1}-bC_t}\right), \tag{14}$$

$$\lambda_t^S = \chi_t V_t \psi L_t^{\eta} + \beta(1-\gamma)\,\mathrm{E}_t\left(\lambda_{t+1}^S\frac{S_{t+1}}{S_t}\right)\,, \tag{15}$$

$$\begin{aligned} 1 = {} & Q_t u_t^I\left[1 - \frac{\kappa_I}{2}\left(\frac{I_t}{I_{t-1}}-1\right)^2 - \kappa_I\left(\frac{I_t}{I_{t-1}}-1\right)\frac{I_t}{I_{t-1}}\right] \\ & + \beta\,\mathrm{E}_t\left[\frac{\lambda_{t+1}^C}{\lambda_t^C}Q_{t+1}u_{t+1}^I\kappa\left(\frac{I_{t+1}}{I_t}-1\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right]\,, \end{aligned} \tag{16}$$

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$$\frac{w_t}{z_t} f_{E,t} = v_t \left[1 - \frac{\kappa_E}{2} \left(\frac{N_{E,t}}{N_{E,t-1}} - 1 \right)^2 - \kappa_E \left(\frac{N_{E,t}}{N_{E,t-1}} - 1 \right) \frac{N_{E,t}}{N_{E,t-1}} \right]$$
$$+ \beta \, \mathrm{E}_t \left[\frac{\lambda_{t+1}^C}{\lambda_t^C} v_{t+1} \kappa_E \left(\frac{N_{E,t+1}}{N_{E,t}} - 1 \right) \left(\frac{N_{E,t+1}}{N_{E,t}} \right)^2 \right], \quad \textbf{(17)}$$

$$r_t^k = Q_t [\delta_1 + \delta_2 (u_t - 1)], \quad \textbf{(18)}$$

$$\lambda_t^C w_t = \mu_t^w \chi_t V_t \psi \eta L_t^{\eta - 1} S_t, \quad \textbf{(19)}$$

where $V_t = (C_t - bC_{t-1} - \psi L_t^\eta S_t)^{-1}$.

2.5. Aggregate Accounting and Data Consistency

The aggregate resource constraint

$$Y_t^C + \frac{w_t}{z_t} f_{E,t} N_{E,t} = w_t L_t + N_t d_t + r_t^k u_t K_{t-1} \quad \textbf{(20)}$$

can be obtained by combining the aggregate budget constraint of households (using $x_t = N_t$) with the government budget constraint $G_t + B_{t-1} = T_t + \frac{B_t}{R_t}$. Government consumption G_t is described by the exogenous AR(1) process $\log G_t = (1 - \rho_g) \log G + \rho_g \log G_{t-1} + \varepsilon_t^G$, where G is the steady state of G_t, and ε_t^G is i.i.d.$N(0, \sigma_{\varepsilon^G}^2)$.

The goods market clearing condition requires aggregate output of final goods Y_t^C to be equal to private and government consumption plus investment in physical capital, i.e., $Y_t^C = C_t + G_t + I_t$. Total investment TI_t is the sum of investment in physical capital and investment in new firms, i.e., $TI_t = I_t + \frac{w_t}{z_t} f_{E,t} N_{E,t}$. The gross domestic product Y_t is equal to Y_t^C plus investment in new firms $\frac{w_t}{z_t} f_{E,t} N_{E,t}$.

The law of motion of the total mass of firms is given by

$$N_t = (1 - \delta) N_{t-1} + (1 - \delta) \left[1 - \frac{\kappa_E}{2} \left(\frac{N_{E,t-1}}{N_{E,t-2}} - 1 \right)^2 \right] N_{E,t-1}. \quad \textbf{(21)}$$

Every period, a fraction of incumbent firms exits the market, where the exit rate δ is assumed to be constant and exogenous. In contrast, the exit rate of newly established firms consists of the exogenous component δ and the endogenous component $\frac{\kappa_E}{2} (\frac{N_{E,t-1}}{N_{E,t-2}} - 1)^2$.

As pointed out by Ghironi and Melitz (2005), empirical measures for the price index are closer to the product price p_t than to the price index P_t for the following two reasons: First, these empirical measures do not update their product space frequently enough to fully account for changes in the number of available products. Second, the construction of these measures is likely not of the functional form present in the translog model. In order to obtain data-consistent real model

TABLE 1. Characteristics of model variants

Model	Competition effect $\xi = -\frac{\partial \mu^p/\mu^p}{\partial N/N}$	Variety effect $\omega = \frac{\partial \rho/\rho}{\partial N/N}$
Translog	$\xi = 1 - \frac{1}{\mu^p}$	$\omega = \frac{1}{2}(\mu^p - 1)$
CES-TrVE	$\xi = 0$	$\omega = \frac{1}{2}(\mu^p - 1)$
CES-NoVE	$\xi = 0$	$\omega = 0$

variables, we thus divide the real model variables by the relative price $\rho_t = p_t/P_t$. Data-consistent real variables are denoted by a superscript r.

2.6. Two Alternative Model Specifications

The above introduced model framework builds on a translog production function as in Feenstra (2003). We denote this model framework as translog or baseline model. In the translog model, the CE ξ and VE ω, evaluated at the deterministic steady state, can be expressed in terms of the steady-state price mark-up: $\xi = 1 - \frac{1}{\mu^p}$ and $\omega = \frac{1}{2}(\mu^p - 1)$.[13]

In this section, we introduce two alternative model specifications that use a CES production function for final goods as in Benassy (1996) that is characterized by constant price mark-ups (and therefore does not feature a CE, $\xi = 0$) and that allows us to freely parameterize the VE.[14] In the first CES specification, the VE is set equal to the value under the translog specification, i.e., $\omega = \frac{1}{2}(\mu^p - 1)$. We denote this the CES-TrVE model. In the second CES specification, the VE is set equal to 0, i.e., $\omega = 0$. We denote this as the CES-NoVE model. Table 1 summarizes the CE and VE in all three model variants, in each case evaluated at the deterministic steady state. In all other respects, the models are identical.

In the following, we estimate the CE and VE. To this end, we log-linearize the translog model around its deterministic steady state and bring the linearized model to the data.[15] The two (log-linearized) CES model variants will later enable us to quantify the importance of the CE and VE in amplifying business cycle fluctuations and to disentangle the CE and VE with the help of counterfactual simulations.

3. INSPECTING THE AMPLIFICATION MECHANISM IN A SIMPLIFIED MODEL

Before moving to the estimation of our model and the quantification of the CE and VE in terms of amplifying business cycle fluctuations, it is instructive to examine the analytics and the intuition of the amplification mechanism in the translog model. To this end, we consider a simplified version of the model that allows us to provide analytical results. For illustration purposes, we limit our analytical

TABLE 2. Linearized model equations in simplified model variant

$\hat{w}_t = (\eta - 1)\hat{L}_t$	Labor supply
$\hat{w}_t = \hat{z}_t + \hat{\rho}_t - \hat{\mu}_t^p$	Labor demand
$\hat{\mu}_t^p = -\xi \hat{N}_t$	Competition effect
$\hat{\rho}_t = \omega \hat{N}_t$	Variety effect
$\hat{C}_t = \hat{w}_t + \hat{L}_t$	Aggregate resource constraint
$\hat{d}_t = \hat{w}_t - \hat{z}_t$	Aggregate free entry condition
$\hat{d}_t + \hat{N}_t = \frac{1}{\mu^p - 1}\hat{\mu}_t^p + \hat{C}_t$	Aggregate profits
$\hat{Y}_t = \frac{\mu^p}{2\mu^p - 1}(\hat{w}_t + \hat{L}_t) + \frac{\mu^p - 1}{2\mu^p - 1}(\hat{d}_t + \hat{N}_t)$	GDP

analysis to labor productivity shocks. All remaining shocks are switched off, i.e., $\chi_t = f_{E,t} = u_t^I = 1$, $G_t = 0$, $\mu_t^w = \mu^w$.

The simplified model assumes instantaneous entry, full depreciation of firms each period ($\delta = 1$) and the absence of entry adjustment costs ($\kappa_E = 0$). This implies that the number of entrants is identical to the number of firms, $N_{E,t} = N_t$, and that the value of a firm equals firm's profits, $v_t = d_t$. We abstract from capital, capital investment and a varying degree of capital utilization. Setting $\alpha = 1$, the aggregate production of intermediate goods simplifies to $N_t y_t = z_t L_t^c$. Inserting the demand function for a single variety $y_t = (\rho_t N_t)^{-1} Y_t^c$ yields the aggregate production function $Y_t^c = z_t \rho_t L_t^c$. If we further abstract from government spending ($G_t = 0$), aggregate demand Y_t^c coincides with private consumption, $Y_t^c = C_t$. The aggregate resource constraint then simplifies to $C_t = w_t L_t$, where we have used the free entry condition $w_t / z_t = v_t$ together with $v_t = d_t$ and $N_t = N_{E,t}$. GDP is the sum of labor and profit income, $Y_t = w_t L_t + d_t N_t$. The simplified model further assumes no habit formation in consumption ($b = 0$) and the limiting case of GHH preferences, $\gamma = 0$, which implies a labor supply equation of the form $w_t = \mu^w \psi \eta L_t^{\eta - 1}$. We proceed by log-linearizing the equilibrium conditions of the simplified model. A hatted variable denotes percentage deviations from the steady state. Table 2 summarizes the model equations that jointly determine $\hat{C}_t$, $\hat{Y}_t$, $\hat{w}_t$, $\hat{L}_t$, $\hat{N}_t$, $\hat{\rho}_t$, $\hat{\mu}_t^p$, and $\hat{d}_t$, given $\hat{z}_t$.

We now provide an analysis of the CE and VE on the dynamics of employment, consumption, and output (GDP) after a rise in labor productivity $\hat{z}_t$. Note that henceforth we use the terms GDP and output interchangeably.[16] Combining labor supply with labor demand to substitute out the real wage and replacing $\hat{\mu}_t^p$ from the definition of the CE and $\hat{\rho}_t$ from the definition of the VE yields the following equation for aggregate employment:

$$\hat{L}_t = \frac{1}{\eta - 1}(\xi + \omega)\hat{N}_t + \frac{1}{\eta - 1}\hat{z}_t . \qquad \textbf{(22)}$$

For a given z and since $\eta > 1$, a rise in the number of firms shifts up the labor demand schedule and raises aggregate employment if the CE and/or the VE are present ($\xi > 0$ and/or $\omega > 0$).

By inserting labor supply into the aggregate resource constraint and by replacing employment $\hat{L}_t$ with equation (22), we obtain consumption as a function of the numbers of the firms and shocks to productivity: $\hat{C}_t = (\xi + \omega)\,\eta/(\eta-1)\hat{N}_t + \eta/(\eta-1)\hat{z}_t$. The data-consistent counterpart $\hat{C}^r_t = \hat{C}_t - \hat{\rho}_t$ is given by

$$\hat{C}^r_t = \frac{1}{\eta - 1}\,(\xi + \eta\omega)\,\hat{N}_t + \frac{\eta}{\eta-1}\hat{z}_t\,. \tag{23}$$

Combining the definition of GDP with the aggregate resource constraint and the equation for aggregate profits, replacing $\hat{\mu}^p_t$ from the definition of the CE, and inserting the equation for $\hat{C}_t$ from above yield $\hat{Y}_t = \omega\eta/(\eta-1)\hat{N}_t + [2\eta(\mu^p - 1) + 1]/[(\eta-1)(2\mu^p - 1)]\xi\hat{N}_t + \eta/(\eta-1)\hat{z}_t$, or in data-consistent terms

$$\hat{Y}^r_t = \frac{1}{\eta-1}\cdot\omega\cdot\hat{N}_t + \frac{2\eta(\mu^p-1)+1}{(\eta-1)(2\mu^p-1)}\cdot\xi\cdot\hat{N}_t + \frac{\eta}{\eta-1}\hat{z}_t\,, \tag{24}$$

where $[2\eta(\mu^p - 1) + 1]/[(\eta-1)(2\mu^p-1)] > 0$ since $\mu^p \geq 1$.

Combining the model equations for labor demand, aggregate free entry, VE, CE, aggregate profits, and using the equation for $\hat{C}_t$ from above yields

$$\hat{N}_t = \frac{\eta}{(\eta-1) - \omega + \frac{\eta-\mu^p}{\mu^p-1}\cdot\xi}\cdot\hat{z}_t\,. \tag{25}$$

A rise in labor productivity leads to a rise in the number of firms if $(\eta-1) - \omega + \frac{\eta-\mu^p}{\mu^p-1}\cdot\xi > 0$, or, inserting $\xi = 1 - \frac{1}{\mu^p}$ and $\omega = \frac{1}{2}(\mu^p - 1)$, if $(\eta-1) - \frac{(\mu^p-1)}{2} + \frac{\eta-\mu^p}{\mu^p} > 0$. For reasonable values of the inverse of the labor supply elasticity, $1-\eta$, and the net steady-state price mark-up, $\mu^p - 1$, this inequality is fulfilled, and we make this assumption for the remainder of this section.

The amplification mechanism is evident from equations (22)–(25). To see this, consider a positive innovation to labor productivity, i.e., $\hat{z}_t > 0$. With $d\hat{N}_t/d\hat{z}_t > 0$, the effects of a rise in labor productivity on employment, consumption, and output are amplified in the presence of the CE and/or VE, i.e., if $\xi > 0$ and/or $\omega > 0$. The stronger the CE and/or VE, the more is the rise in economic activity after a positive innovation to productivity.

To understand the effects of a rise in labor productivity, assume for the moment that the number of firms stays constant (i.e., $\hat{N}_t = 0$, implying $\hat{\rho}_t = \hat{\mu}^p_t = 0$). The rise in labor productivity shifts up the labor demand curve by $\hat{z}_t$ along an unchanged labor supply curve such that wages and employment rise. The increased income creates an additional demand for goods ($\hat{C}_t = \hat{w}_t + \hat{L}_t > 0$). The rise in consumption raises profits above entry costs, which provides an incentive for new firms to enter the market (note that for $\hat{N}_t = 0$, $\hat{d}_t = \hat{C}_t$ and $\hat{w}_t - \hat{z}_t = 0$). As a consequence, the number of firms and products rises ($\hat{N}_t > 0$). With a rising number of firms, profits per firm fall until the free entry condition is restored

($\hat{d}_t = \hat{w}_t - \hat{z}_t$). The rise in labor income and the rise in aggregate profits raise output ($\hat{Y}_t > 0$).

How does the rise in the number of firms amplify output fluctuations? In the presence of the CE (i.e., if $\xi > 0$), goods become closer substitutes as the number of varieties rises. Hence, the elasticity of substitution between different varieties increases and price mark-ups decline. The fall in price mark-ups leads to a further upward shift of the labor demand curve that magnifies the initial rise in wages and employment. This translates into an amplification of the output response after a favorable labor productivity shock relative to the case of constant price mark-ups (i.e., if $\xi = 0$).

In the presence of the VE (or increasing returns to specialization, i.e., if $\omega > 0$), an increase in the number of intermediate goods raises the productivity of any of the intermediate goods used in the production of final goods. This endogenous rise in the productivity of final goods production lowers the price of final goods relative to the price of intermediate goods ($\hat{\rho}_t > 0$). The labor demand curve shifts up by $\hat{\rho}_t$. Thus, the increase in employment, real wages, and output in response to a labor productivity shock is stronger than without the VE.

A necessary condition for firm entry to amplify output fluctuations is a positive co-movement of output and the number of firms. In our example of a positive innovation to labor productivity within our simplified model variant, this happens under very mild parameter restrictions. If, on the other hand, a favorable shock (a shock that raises output) leads to a decline in firm entry and the number of firms, the outlined amplification mechanism turns into a dampening mechanism. The reason is that a decrease in the number of firms raises price mark-ups through the CE and raises the price of final goods relative to the price of intermediate goods through the VE.

In Section 6, we use the estimated baseline model to analyze the conditional dynamics of firm entry and output in response to various shocks and to quantify the strength of the CE and VE in amplifying or attenuating output fluctuations.

4. DATA AND ESTIMATION PROCEDURE

This section describes the data set and the estimation procedure we use to estimate the translog model. Following An and Schorfheide (2007) and Smets and Wouters (2007), we estimate a subset of the model parameters using Bayesian techniques. For the estimation, we use seven time series of U.S. quarterly data: the growth rates of real per capita GDP, consumption, and investment, the logarithm of per capita hours worked, the growth rates of two measures of real wages, and the growth rate of per capita new firms.

As empirical measure for firm entry, we use the data series of new business incorporations (NBI) from the Survey of Current Businesses published by the Bureau of Economic Analysis.[17] We define consumption as consumption expenditures on non-durables and services and investment as the sum of consumption expenditures on durables, fixed private investments, and changes in private inventories. Following Justiniano et al. (2013) and Gali et al. (2012), we use two empirical wage measures: hourly compensation in the non-farm business sector and average hourly earnings of production and non-supervisory employees. Both measures are taken from the Bureau of Labor Statistics. A full description of the data sources and the construction of the data series can be found in the data appendix. The data sample starts in 1964:Q1 and ends in 2012:Q2. Due to limited data availability, the new firm series ends in 1998:Q3.[18]

The measurement equations for GDP, consumption, investment, hours worked, and entry then read as follows:[19]

$$\begin{pmatrix} dl(\mathrm{GDP}_t) \\ dl(\mathrm{CONS}_t) \\ dl(\mathrm{INV}_t) \\ l(\mathrm{HOURS}_t) \\ dl(\mathrm{ENTRY}_t) \end{pmatrix} = \begin{pmatrix} \Delta \hat{Y}_t^r \\ \Delta \hat{C}_t^r \\ \Delta \hat{T} \hat{I}_t^r \\ \hat{L}_t \\ \Delta \hat{N}_{E,t} \end{pmatrix} \times 100.$$

The functions l and dl stand for 100 times the demeaned logarithm and the demeaned log-difference, respectively. A hat denotes log-deviations from the steady state and Δ is the time-difference operator.

To include the information of both wage measures, we set up the following measurement equation:

$$\begin{pmatrix} dl\mathrm{WAGE1}_t \\ dl\mathrm{WAGE2}_t \end{pmatrix} = \begin{pmatrix} 1 \\ \lambda \end{pmatrix} \Delta \hat{w}_t^r + \begin{pmatrix} \varepsilon_t^{w1,me} \\ \varepsilon_t^{w2,me} \end{pmatrix},$$

where λ denotes the loading coefficient for the second wage series. Since both loadings are not separately identified, we set the first loading coefficient to unity. $\varepsilon_t^{w1,me}$ and $\varepsilon_t^{w2,me}$ are two measurement errors, which are i.i.d.$N(0, \sigma^2_{\varepsilon^{w1,me}})$ and i.i.d.$N(0, \sigma^2_{\varepsilon^{w2,me}})$, respectively. $\Delta \hat{w}_t^r$ can be interpreted as latent factor, which captures the common movement in both wage series. The two error terms capture the idiosyncratic fluctuations in the wage series.[20]

The application of seven data series requires at least seven exogenous disturbances. In total, the model is governed by eight disturbances, including innovations to government consumption ε_t^g, to labor productivity ε_t^z, to investment-specific technology ε_t^I, to entry costs $\varepsilon_t^{f_E}$, to preferences ε_t^χ, and to the wage mark-up $\varepsilon_t^{\mu^w}$, plus the two measurement errors $\varepsilon_t^{w1,me}$ and $\varepsilon_t^{w2,me}$.

A subset of parameters is calibrated as summarized in Table 3. The discount rate β is set to 0.99, implying an annual steady-state interest rate of approximately 4%. The steady-state value for the utilization rate u is set to unity, implying the steady-state value of the depreciation rate δ^K to be equal to δ_0. For the latter, we choose a standard value of 0.025. Following Chugh and Ghironi (2015), the potential mass of firms in the economy $\tilde{N}$ is assumed to be 10^9. The exogenous firm exit rate δ is set to 0.025, as in Bilbiie et al. (2012). The steady-state values

TABLE 3. Calibrated parameters

Parameter	Value	Definition
β	0.99	Discount factor
δ_0	0.025	Steady-state capital depreciation rate
δ	0.025	Steady-state firm exit rate
u	1	Steady-state capacity utilization rate
μ^w	1.2	Steady-state wage mark-up
G/Y	0.18	Steady-state ratio of government consumption to GDP
L	0.25	Steady state of hours worked
$\tilde{N}$	10^9	Potential mass of firms

G/Y and L are set to 0.18 and 0.25, respectively. Following Gali et al. (2012), we set the steady-state wage mark-up μ^w at 20%.

The remaining parameters are estimated. Table 4 summarizes the prior distributions. Our choice of distributions is in line with the literature and mainly results from different distributional supports. The probability mass of the inverse gamma distribution is distributed over the interval $(0, \infty)$, the gamma distribution over the interval $[0, \infty)$, the beta distribution over the interval $[0, 1]$, and the normal distribution over the interval $(-\infty, \infty)$.

The standard deviation of the innovations is assumed to follow an inverse gamma distribution with mean 0.02 and standard deviation 1. For the autocorrelation parameters of the exogenous shock processes, we choose a beta distribution with mean 0.5 and standard deviation 0.2. The moving average coefficient of the wage mark-up shock is assumed to follow a normal distribution with mean 0 and standard deviation 0.2.

The prior distributions for the structural parameters related to firm entry are given as follows. For the steady-state price mark-up μ^p, we use a truncated gamma distribution, where we only allow for values greater than 1.01. It has mean 1.3 and standard deviation 0.2. The 90% probability interval of this distribution then ranges from 1.04 to 1.68. For the entry adjustment cost parameter κ_E, we use the same prior distribution as for the investment adjustment cost parameter, i.e., a gamma distribution with mean 4.0 and standard deviation 1.0. For the prior distribution of the remaining structural parameters, we broadly follow the existing literature.

5. ESTIMATION RESULTS

In this section, we first present the parameter estimates. Next, we discuss the model's predictions regarding volatility, autocorrelations, and cross-correlations of the time series included as observables. Then, we discuss the contribution of each of the structural shocks to the forecast error variance of the endogenous variables at business cycle frequency.

TABLE 4. Results from the Bayesian estimation including prior distribution and probability intervals

		Prior distribution			Posterior distribution	
Parameter		Type	Mean	Std	Mean	[5% , 95%]
Structural parameters						
Labor share in production	α	Beta	0.7	0.2	0.85	[0.81, 0.90]
Labor utility	θ	Gamma	2.0	1.0	3.64	[1.92, 5.80]
Wealth elasticity of labor supply	γ	Beta	0.5	0.2	0.79	[0.63, 0.93]
Consumption habit	b	Beta	0.5	0.2	0.76	[0.71, 0.80]
Investment adjustment cost	κ_I	Gamma	4.0	1.0	3.82	[2.59, 5.28]
Inverse elasticity of capital utilization	$\frac{\delta_2}{\delta_1}$	Igamma	1.0	1.0	0.55	[0.33, 0.89]
Price mark-up	μ^p	Gamma	1.3	0.2	1.26	[1.16, 1.36]
Entry adjustment cost	κ_E	Gamma	4.0	1.0	1.50	[1.09, 1.99]
Autocorrelation of shock processes						
Labor productivity	ρ_z	Beta	0.5	0.2	0.96	[0.94, 0.98]
Wage mark-up	ρ_μ	Beta	0.5	0.2	0.97	[0.95, 0.98]
Investment-specific technology	ρ_I	Beta	0.5	0.2	0.24	[0.12, 0.38]
Government spending	ρ_G	Beta	0.5	0.2	0.92	[0.88, 0.94]
Entry cost	ρ_{f_E}	Beta	0.5	0.2	0.95	[0.91, 0.98]
Standard deviation of innovations						
Labor productivity	σ_{ε^z}	Igamma	2.0	1	0.80	[0.70, 0.90]
Wage mark-up	σ_{ε^μ}	Igamma	2.0	1	4.30	[3.00, 5.95]
Investment-specific technology	σ_{ε^I}	Igamma	2.0	1	3.99	[2.39, 6.54]
Preference	$\sigma_{\varepsilon^\chi}$	Igamma	2.0	1	1.46	[1.07, 1.91]
Government spending	σ_{ε^G}	Igamma	2.0	1	1.87	[1.71, 2.03]
Entry cost	$\sigma_{\varepsilon^{f_E}}$	Igamma	2.0	1	2.43	[1.96, 2.97]
Moving average parameter and loading coefficient						
Wage mark-up shock	ν	Normal	0.0	0.2	0.41	[0.26, 0.56]
Loading coefficient	λ	Normal	1.0	2.0	0.13	[0.06, 0.19]

Notes: Using a Random Walk Metropolis–Hastings algorithm, we generate two chains of 2 millions parameter draws each. For each chain, we discard the first 1 Mio. draws and use the remaining draws to compute the posterior mean and percentiles.

5.1. Parameter Estimates

Table 4 displays the estimated parameters as means of the posterior distribution and the 90% probability intervals obtained by the Metropolis–Hastings algorithm.

To start with, we focus on the parameters related to the entry mechanism. The gross price mark-up μ^p is estimated to be significantly different from one. The point estimate implies a steady-state mark-up of 26% with a probability band ranging from 16% to 36%. The point estimate of μ^p is close to the value of 1.22 reported in Lewis and Stevens (2015). However, it is significantly smaller than the value of 1.66 reported in Lewis and Poilly (2012). Regarding the CE and VE, the point estimate of μ^p implies that a 1% increase in the mass of firms lowers the price mark-up by 0.21% (the CE ξ) and raises the relative price by 0.13% (the VE ω). CE and VE are statistically significantly different from 0 with confidence bands for ξ and ω ranging from 1.14 to 1.26 and 0.08 to 0.18, respectively.[21]

Entry adjustment costs κ_E are estimated to be 1.5 with a probability interval ranging from 1.09 to 1.99. This is significantly lower than the 3.82 point estimate for the investment adjustment cost parameter κ_I. As discussed below, the model overestimates both the volatility of firm entry and its first-order autocorrelation. Higher entry adjustment costs would help to bring the model closer to the empirical standard deviation of firm entry but only at the cost of an even higher autocorrelation.

Turning to the other structural parameters, θ, which determines the labor supply elasticity, is estimated at 3.64 with a relatively wide probability interval ranging from 1.92 to 5.80. The point estimate of the wealth elasticity of labor supply γ is 0.79 with a probability interval ranging from 0.63 to 0.93, implying that preferences are close to those in King et al. (1988). This is in contrast to the results of Schmitt-Grohé and Uribe (2012), who estimate a near-zero wealth elasticity of labor supply in a theoretical environment that abstracts from endogenous firm entry and in which shocks feature an anticipated component. The labor share in production α is estimated at 0.85 with a probability interval ranging from 0.81 to 0.90. Note that this estimate is not comparable to the estimates of standard DSGE models without firm entry since in our model, in which labor is utilized in the manufacturing sector and in the creation of new products, α is not equal to the labor share in GDP. For the latter, our point estimate implies a standard value of 72%.

Regarding the exogenous shock processes, we find that shocks to labor productivity, to wage mark-ups, to government spending, and to entry costs are estimated to be highly persistent with AR(1) coefficients all above 0.9. In contrast, the persistence parameter of the investment-specific technology shock is relatively low with a value of 0.24, implying that the investment-specific technology shock explains less forecast-error variance at higher forecast-horizons.

In the following, we compute the model's predictions about the second moments, variance decomposition, impulse responses, and amplification measures at the posterior mean reported in Table 4. To compute the corresponding probability bands, we use the last 50,000 parameter draws of the Metropolis–Hastings algorithm and compute the respective moments for each draw.

5.2. Second Moments and Variance Decomposition

In order to assess the performance of the model in fitting the data, we compare the model-implied second moments to the corresponding empirical moments of the data. Table 5 reports standard deviations, relative standard deviations, first-order autocorrelations, and contemporaneous correlations with the growth rate of GDP. The model-implied moments are derived from simulated data, where the measurement errors are turned off during the simulation.

The empirical moments of GDP, consumption, total investment, and hours worked are matched quite well. Concerning firm entry growth, the estimated model captures the observed procyclicality of firm entry. However, the model overstates its volatility and its serial correlation. This is attributable to the fact that we model an endogenous failure rate of firms as an increasing function of the change in firm entry. This mechanism is introduced to dampen the volatility of firm entry. However, it also generates substantial persistence in firm entry. As mentioned above, this trade-off between volatility and autocorrelation explains the small point estimate of the entry adjustment cost parameter κ_E, compared to the capital adjustment cost parameter κ_I.[22]

Table 6 shows the mean forecast-error variance decomposition of GDP, consumption, total investment, hours worked, wages, and firm entry at business cycle frequencies ranging from 6 to 32 quarters. Most variations are explained by labor productivity and wage mark-up shocks. Together they account for more than 75% of the variations in GDP, consumption, total investment, hours worked, and wages. The investment-specific technology shock explains 21% of the variations in total investment. The firm entry cost shock accounts for most variations in firm entry. The government spending and the preference shock are only of minor importance for the variables under consideration.

The importance of wage mark-up and labor productivity shocks in driving business cycle fluctuations is consistent with the findings in Smets and Wouters (2007) but stands in contrast to Justiniano et al. (2010), who find that most of the variations in GDP is due to shocks to investment-specific technology. The discrepancy between Smets and Wouters (2007) and Justiniano et al. (2010) stems from different definitions of investment and consumption. The latter define purchases of consumer durables and changes in inventories as part of investment, whereas the former define purchases of consumer durables as part of consumption and exclude changes in inventories from investment. Interestingly, we find that investment-specific technology shocks are minor contributors to business cycle fluctuations, although we adopt the same definition of consumption and investment as Justiniano et al. (2010).[23]

We argue that the difference in the importance of the investment-specific technology shock is (at least partly) due to the endogenous firm entry mechanism that is absent in the above mentioned papers. In our framework, shocks to the efficiency with which final goods can be transformed into physical capital—in contrast to wage mark-up and labor productivity shocks—are not able to replicate

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TABLE 5. Second moments

		Std (σ_X)			1st-order autocorr.		
			Model			Model	
	X	Data	Mean	[5%, 95%]	Data	Mean	[5%, 95%]
GDP growth	$\Delta \hat{Y}^r$	0.86	0.85	[0.80, 0.89]	0.31	0.31	[0.27, 0.37]
Consumption growth	$\Delta \hat{C}^r$	0.55	0.59	[0.54, 0.63]	0.42	0.39	[0.32, 0.46]
Investment growth	$\Delta \widehat{TI}^r$	3.27	3.43	[3.11, 3.56]	0.31	0.26	[0.21, 0.35]
Hours worked	$\hat{L}$	5.05	4.16	[3.40, 5.59]	0.98	0.98	[0.97, 0.99]
Wage growth (1st series)	$\Delta \hat{w}^r$	0.61	0.69	[0.64, 0.75]	0.06	0.11	[0.07, 0.15]
Wage growth (2nd series)		0.36			0.56		
Firm entry growth	$\Delta \hat{N}_E$	3.10	4.30	[3.84, 4.85]	−0.02	0.53	[0.47, 0.60]
		Rel. std. ($\sigma_X/\sigma_{\Delta \hat{Y}^r}$)			Contemp. $corr(X, \Delta \hat{Y}^r)$		
			Model			Model	
	X	Data	Mean	[5%, 95%]	Data	Mean	[5%, 95%]
Consumption growth	$\Delta \hat{C}^r$	0.63	0.69	[0.64, 0.75]	0.59	0.53	[0.49, 0.61]
Investment growth	$\Delta \widehat{TI}^r$	3.80	4.01	[3.73, 4.15]	0.86	0.84	[0.81, 0.86]
Hours worked	$\hat{L}$	5.87	4.87	[4.04, 6.57]	0.14	0.11	[0.08, 0.13]
Wage growth (1st series)	$\Delta \hat{w}^r$	0.71	0.82	[0.76, 0.89]	0.03	0.51	[0.44, 0.56]
Wage growth (2nd series)		0.42			0.31		
Firm entry growth	$\Delta \hat{N}_E$	3.43	5.03	[4.53, 5.82]	0.20	0.27	[0.23, 0.38]

Notes: Mean values are computed by simulating the model at the posterior mean reported in Table 4. To compute the corresponding percentiles, we only use the last 50,000 parameter draws (25,000 of each chain). For each parameter draw, we simulate the model and compute the second moments.

Table 6. Variance decomposition at business cycle frequency

		Labor productivity	Wage mark-up	Investment-specific technology	Preference	Government spending	Entry cost
GDP	Y^r	31.4	62.8	4.7	0.1	0.6	0.4
		[23.7 , 40.2]	[53.6 , 71.3]	[2.7 , 6.8]	[0.0 , 0.1]	[0.4 , 0.8]	[0.2 , 1.0]
Consumption	C^r	28.5	60.4	2.8	1.8	2.4	4.1
		[19.0 , 40.7]	[47.3 , 72.5]	[1.3 , 4.5]	[1.0 , 2.7]	[1.2 , 4.5]	[1.5 , 6.3]
Total invest.	TI^r	25.9	48.6	15.6	0.6	1.5	7.8
		[20.6 , 32.7]	[42.3 , 56.4]	[10.2 , 20.8]	[0.4 , 1.0]	[1.0 , 2.1]	[3.9 , 12.2]
Hours	L	0.5	97.4	0.7	0.0	0.3	1.0
		[0.3 , 0.8]	[95.3 , 98.6]	[0.4 , 1.2]	[0.0 , 0.0]	[0.2 , 0.7]	[0.4 , 2.2]
Wages	w^r	88.1	2.1	2.3	0.2	0.2	7.2
		[83.4 , 92.4]	[1.4 , 3.2]	[1.0 , 3.9]	[0.1 , 0.3]	[0.1 , 0.2]	[3.8 , 11.2]
Firm Entry	N_E	10.4	18.9	4.9	0.4	0.6	64.9
		[7.5 , 14.4]	[13.6 , 25.9]	[2.6 , 7.5]	[0.2 , 0.7]	[0.3 , 0.9]	[54.1 , 74.1]

Notes: Main figures are computed at the posterior mean reported in Table 4. Figures in brackets give the corresponding 5th and 95th percentiles. To compute these percentiles, we use the last 50,000 parameter draws (25,000 of each chain). For each parameter draw, we simulate the model and compute the variance decomposition. To obtain the variance decompositions at business cycle frequency, we compute variance decomposition for the forecast horizons 6–32 and take the mean. Shares may not add up to 100 due to rounding.

the positive co-movement between firm entry and other key variables in the data. On the contrary, an expansionary investment-specific technology shock induces a drop in investments into new firms, as discussed below. This explains why the investment-specific technology shock is estimated to be of minor importance.[24]

6. THE AMPLIFICATION MECHANISM IN THE ESTIMATED MODEL

This section analyzes the amplification mechanism of endogenous firm entry in the estimated translog model. In order to identify the amplification mechanism and to disentangle the impact of the CE and VE on the model dynamics, we compare the first and second conditional moments of the three introduced model variants (see Section 2.6): the estimated translog model and the two counterfactuals where either the CE is switched off (denoted as CES-TrVE model) or both effects are switched off (denoted as CES-NoVE model). For both CES models, we keep the parameter estimates from the translog model.

We proceed in two steps. First, we show that the way firm entry affects the model dynamics is shock dependent. As discussed in Section 3, changes in firm entry amplify output fluctuations through the CE and VE if the correlation between GDP and firm entry (or the number of firms) conditional on a specific shock is positive. Contrarily, if the conditional correlation between output and the number of firms is negative, firm entry dampens output fluctuations. We find that shocks to labor productivity, wage mark-ups, and preferences generate a positive correlation between GDP and the number of firms, see Table 7 below. In contrast, shocks to aggregate demand (government spending) and to investment-specific technology induce a negative co-movement of output and the number of firms.[25] In order to illustrate that the amplification mechanism can turn into a dampening mechanism, we present exemplarily impulse responses for two shocks: (i) a shock to labor productivity and (ii) a shock to investment-specific technology. The full set of impulse responses to the remaining four structural shocks is discussed in Supplementary Appendix B.1.[26]

In the second step, we show that, overall, firm entry amplifies output fluctuations via counteryclical price mark-ups and increasing returns to specialization. The reason is that the most important shocks in driving business cycle fluctuations (wage mark-up and labor productivity shock) induce a procyclical movement of the number of firms. Moreover, we quantify the amplification mechanism embedded in the endogenous entry model by comparing shock-specific and overall volatility measures across the three model frameworks.

6.1. Impulse Responses

Figure 1 shows the impulse responses of GDP, consumption, total investment, entry costs, the price mark-up, firm entry, profits per firm, average output of an individual firm, real wages, and the real interest rate to a positive technology shock z_t. All real variables are shown using the data-consistent deflator p_t. Impulse

TABLE 7. Standard deviations, relative volatilities, and amplification indicators

	Volatility			Amplification			*Corr*
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	(X, N)
Std of GDP relative to . . . shock							$X = Y^r$
Labor prod.	1.0006	0.9332	0.9171	9.1%	7.2%	1.8%	0.92
	[0.9550, 1.0309]	[0.8956, 0.9616]	[0.8815, 0.9452]	[6.5%, 10.8%]	[4.8%, 9.0%]	[1.1%, 2.1%]	
Wage mark-up	0.1811	0.1690	0.1661	9.0%	7.2%	1.8%	0.93
	[0.1287, 0.2620]	[0.1201, 0.2456]	[0.1180, 0.2418]	[6.3%, 10.8%]	[4.7%, 9.0%]	[1.1%, 2.1%]	
Investment-specific	0.2166	0.2281	0.2317	−6.5%	−5.0%	−1.6%	−0.55
technology	[0.1341, 0.3413]	[0.1420, 0.3547]	[0.1438, 0.3605]	[−7.9%, −4.2%]	[−6.5%, -2.9%]	[−1.8%, −1.0%]	
Preference	0.0749	0.0735	0.0736	1.8%	2.0%	−0.2%	0.14
	[0.0582, 0.0923]	[0.0568, 0.0911]	[0.0568, 0.0914]	[0.0%, 3.9%]	[0.6%, 3.5%]	[−0.8%, 0.5%]	
Government spending	0.0627	0.0639	0.0643	−2.5%	−2.0%	−0.6%	−0.16
	[0.0516, 0.0757]	[0.0530, 0.0769]	[0.0533, 0.0772]	[−5.1%, −0.2%]	[−4.3%, −0.1%]	[−1.0%, 0.0%]	
Absolute std of GDP							
All five shocks	0.0521	0.0488	0.0480	8.5%	6.8%	1.6%	0.56
	[0.0438, 0.0682]	[0.0410, 0.0644]	[0.0404, 0.0635]	[6.1%, 10.1%]	[4.5%, 8.4%]	[1.0%, 2.0%]	

TABLE 7. Continued

	Volatility			Amplification			
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	*Corr* (X, N)
Std of consumption relative to . . . shock							$X = C^r$
Labor prod.	1.0705	0.9287	0.8846	21.0%	15.3%	5.0%	0.97
	[0.9284, 1.2317]	[0.8041, 1.0797]	[0.7667, 1.0288]	[14.0%, 26.4%]	[10.1%, 19.4%]	[3.5%, 6.1%]	
Wage mark-up	0.1995	0.1741	0.1659	20.2%	14.6%	4.9%	0.97
	[0.1416, 0.2909]	[0.1221, 0.2584]	[0.1160, 0.2478]	[12.7%, 27.1%]	[9.0%, 20.0%]	[3.4%, 6.1%]	
Investment-specific	0.2797	0.2954	0.3034	−7.8%	−5.3%	−2.7%	−0.49
technology	[0.1680, 0.4293]	[0.1801, 0.4471]	[0.1852, 0.4583]	[−10.8%, −5.2%]	[−7.9%, −3.1%]	[−3.4%, −1.9%]	
Preference	0.2915	0.2962	0.2948	−1.1%	−1.6%	0.5%	−0.15
	[0.2626, 0.3215]	[0.2670, 0.3266]	[0.2651, 0.3255]	[−1.8%, −0.5%]	[−2.2%, −1.0%]	[0.3%, 0.7%]	
Government spending	0.1461	0.1327	0.1297	12.7%	10.1%	2.3%	0.95
	[0.1213, 0.1741]	[0.1090, 0.1615]	[0.1063, 0.1584]	[7.2%, 17.6%]	[5.7%, 14.2%]	[1.4%, 3.1%]	
Absolute std of consumption							
All five shocks	0.0577	0.0507	0.0486	18.7%	13.7%	4.4%	0.55
	[0.0466, 0.0802]	[0.0406, 0.0721]	[0.0389, 0.0693]	[12.3%, 23.3%]	[8.8%, 17.3%]	[3.2%, 5.4%]	

Table 7. Continued

	Volatility			Amplification			*Corr*
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	(X, N)
Std of total investment relative to . . . shock							$X = TI^r$
Labor prod.	2.2082	2.3363	2.2656	−2.5%	−5.5%	3.1%	0.67
	[1.7058, 2.5469]	[1.8696, 2.6440]	[1.8251, 2.5616]	[−7.5%, 1.0%]	[−9.5%, −2.5%]	[2.0%, 3.9%]	
Wage mark-up	0.3743	0.3982	0.3865	−3.1%	−6.0%	3.0%	0.68
	[0.2556, 0.5564]	[0.2728, 0.5918]	[0.2650, 0.5731]	[−6.7%, −0.3%]	[−8.8%, −3.6%]	[2.1%, 3.8%]	
Investment-specific	1.2574	1.2366	1.2448	1.0%	1.7%	−0.7%	−0.12
technology	[0.7753, 2.0362]	[0.7620, 2.0099]	[0.7654, 2.0247]	[−0.1%, 2.2%]	[0.7%, 2.7%]	[−1.0%, −0.3%]	
Preference	0.5985	0.6094	0.6004	−0.3%	−1.8%	1.5%	0.34
	[0.5303, 0.6943]	[0.5389, 0.7079]	[0.5297, 0.6987]	[−1.5%, 1.1%]	[−2.7%, −0.6%]	[1.1%, 1.9%]	
Government spending	0.3138	0.3231	0.3155	−0.5%	−2.9%	2.4%	0.52
	[0.2423, 0.3679]	[0.2518, 0.3759]	[0.2463, 0.3676]	[−3.1%, 1.7%]	[−5.0%, −0.9%]	[1.8%, 2.9%]	
Absolute std of total investment							
All five shocks	0.1203	0.1261	0.1231	−2.3%	−4.6%	2.5%	0.44
	[0.1079, 0.1375]	[0.1134, 0.1436]	[0.1109, 0.1401]	[−5.3%, 0.0%]	[−7.0%, −2.7%]	[1.7%, 3.1%]	

Notes: Volatilities and amplification measures are computed by simulating the model at the posterior mean reported in Table 4. Figures in brackets give the corresponding 5th and 95th percentiles. To compute these percentiles, we use the last 50,000 parameter draws (25,000 of each chain). For each parameter draw, we simulate the models and compute the volatility and amplification measures. The contemporaneous correlation in the last column is based on simulated data from the translog model at the posterior mean.

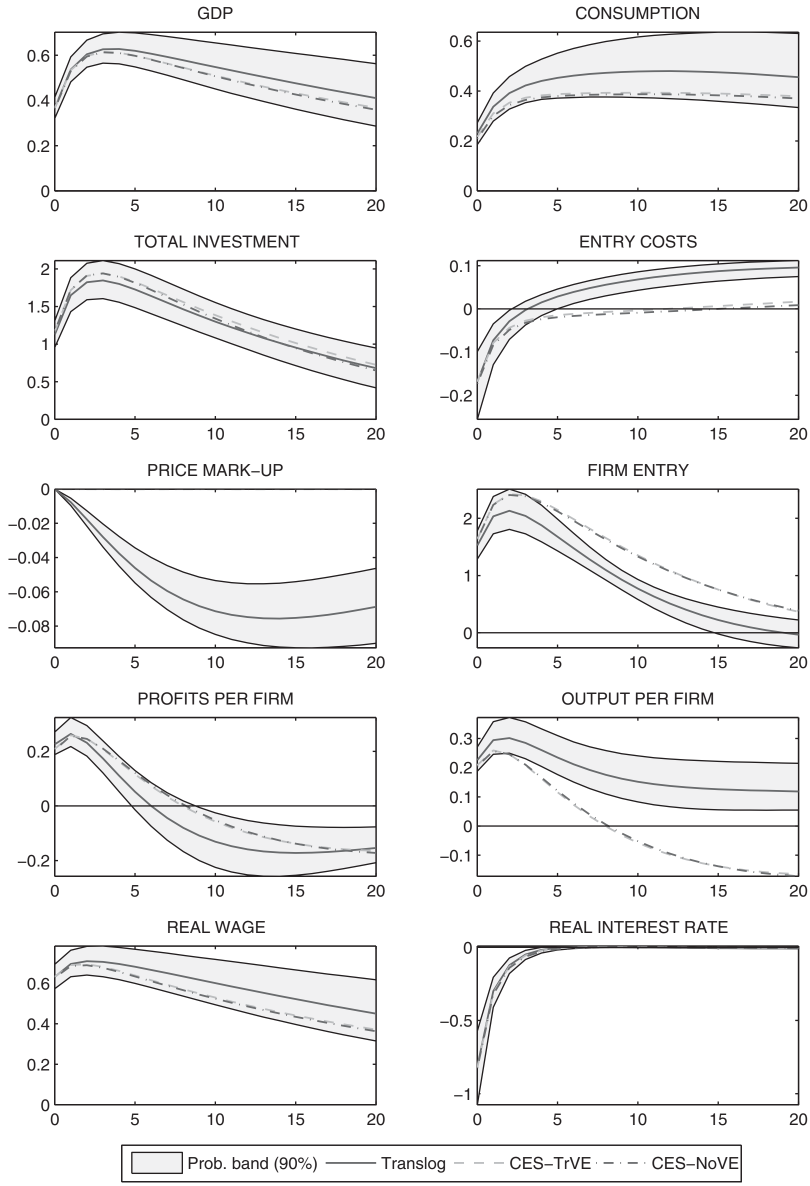

FIGURE 1. Impulse responses to a labor productivity shock.

responses are measured as percentage deviations from steady states. The solid lines show impulse responses of the estimated translog model, the dashed lines show responses of the CES-TrVE model with the CE switched off, and the dashed-dotted lines show responses of CES-NoVE model with CE and VE switched off.

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The shaded areas are the 90% probability bands that reflect parameter uncertainty in the translog model.

A rise in labor productivity raises GDP, consumption, as well as both components of total investment, investment in physical capital (not shown here) and in firm entry. Firm entry is fueled by rising profit opportunities of monopolistic firms due to the increase in aggregate demand as well as by the drop in entry costs. The latter decreases since the increase in z_t outweighs the rise in real wages. Hence, the mass of firms (or products) starts to increase. In the presence of the CE, this makes products closer substitutes and thus deteriorates market power in the monopolistic sector. This leads to a decrease in price mark-ups that boosts aggregate demand and induces individual firms to further increase their production. The increase in aggregate demand is enforced by the drop in the welfare-relevant price index if the VE is present.

The magnification effect is evident in the impulse response functions. The CE and to a much lesser extent the VE magnify the effects of productivity shocks on GDP and, in particular, on consumption. Total investment, however, is dampened. Since investment in physical capital is also amplified, this can only be explained by a dampening of firm entry. The latter is caused by the rise in entry costs over the medium run due to rising real wages and by the fall in price mark-ups, which, in isolation, deteriorates profit opportunities of monopolistic firms. Note that the probability band does not give implications about the significance of the amplification mechanism. If the counterfactual CES responses lie inside the probability region, this does not imply that the amplification mechanism is insignificant. In order to give implications about the significance of the amplification mechanism, one needs to take into account the parameter uncertainty in all three model frameworks. This is done in Section 6.2.

To sum up, it is mainly the CE that amplifies, via countercyclical price mark-ups, the impact of labor-augmenting technology shocks on GDP and consumption. However, countercyclical price mark-ups dampen the responses of firm entry, which translates into a dampening of total investment.

Figure 2 shows the responses to a favorable investment-specific technology shock.

An increase in the efficiency with which final goods can be transformed into physical capital produces a boom in capital investment and a hike in GDP. Consumption falls on impact but turns positive during the course of adjustment. Real wages and thus entry costs increase. The value of a firm v_t decreases due to the increase in the real interest rate, which outweighs the increase in individual firm's profits. Consequently, investments into the capital stock of existing firms are more profitable than investments into new firms such that firm entry falls. Thus, the estimated conditional correlation between firm entry and GDP is negative for the investment-specific technology shock. This implies that, in the presence of the CE, the market power of firms and thus price mark-ups increase, which abates the impacts of investment-specific technology shocks on GDP and consumption. In the presence of the VE, a decrease in the number of firms raises the price of final

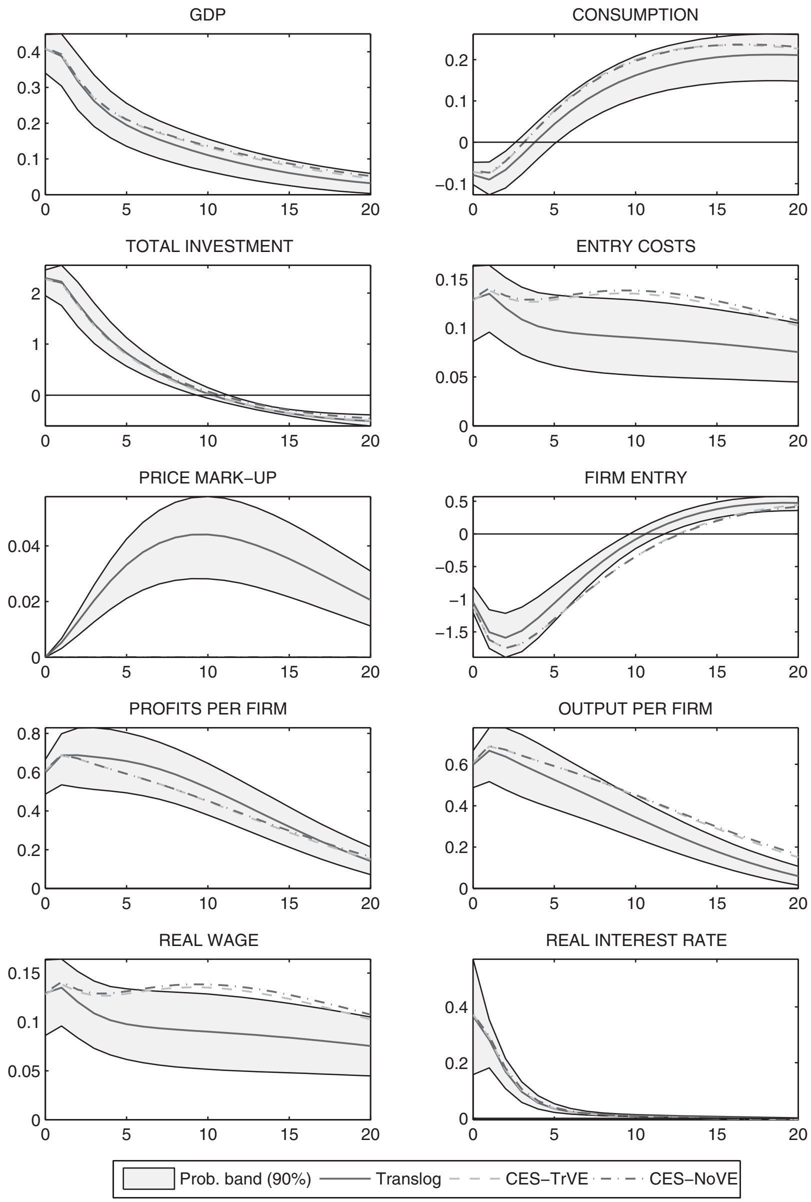

FIGURE 2. Impulse responses to an investment-specific technology shock.

goods relative to the price of intermediate goods, which dampens the rise in GDP and consumption after an investment-specific technology shocks. Note, though, that the impacts of the VE on the model dynamics are much less pronounced compared to the CE. Thus, it is mainly the CE that dampens, via procyclical

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price mark-ups, the impact of investment-specific technology shocks on GDP and consumption.

6.2. Quantifying the Internal Amplification Mechanisms

In this section, we quantify the amplification mechanism embedded in the entry model and assess the contribution of the CE and VE. Following Jaimovich and Floetotto (2008), we consider overall and shock-specific amplification measures, including shocks to labor productivity, to wage mark-ups, to investment-specific technology, to preferences, and to government spending.

In order to quantify the amplification mechanism, we proceed in two steps. In the first step, we simulate the three model frameworks (translog model, CES-TrVE model, and CES-NoVE model) and compute shock-specific and overall volatility measures. As in the analysis of the impulse responses, we keep the parameter estimates from the translog model when simulating the CES models.[27] Based on the simulated volatility measures, we compute, in the second step, three amplification metrics. The total amplification through both the CE and VE is measured as the volatility difference, in percentage terms, between the translog model and the CES-NoVE model. The contribution of the CE is measured by the volatility difference, in percentage terms, between the translog model and the CES-TrVE model. Analogously, the contribution of the VE is computed as the volatility difference, in percentage terms, between the CES-TrVE model and the CES-NoVE model. Note that the contributions of the CE and VE do not necessarily add up to the total amplification since they are computed on different bases. Table 7 shows our results. The volatility and amplification measures are computed at the posterior mean reported in Table 4. Numbers in brackets give the corresponding 5th and 95th percentiles.

To start with, we focus on GDP. The results are displayed in the upper panel of Table 7. The shock-specific and overall volatility measures are shown in columns 1–3. Shock-specific volatilities are obtained by assuming that, at each time, only one of the above mentioned shocks is active. We then compute, for all three model frameworks and for all five shocks under consideration, the standard deviation of GDP relative to the standard deviation of the underlying shock process.[28] The overall volatility is measured by the absolute standard deviations of GDP when all five considered structural shocks are active. Columns 4–6 show the amplification ratios measured in percentage points. The last column reports the contemporaneous correlation between the number of firms and GDP.

When all five shocks are active, the volatility of GDP under translog preferences is substantially higher than under the two CES models. In total, GDP is amplified by 8.5% with a 90% probability band ranging from 6.1% to 10.1%. The CE accounts for most amplification across all shocks. Overall, the CE increases the volatility of GDP by 6.8% with a probability band ranging from 4.5% to 8.4%. The increase through the VE, on the other hand, only amounts to 1.6% with a probability band ranging from 1.0% to 2.0%.

Turning to the shock-specific amplification ratios, we obtain the following results. Productivity shocks are amplified by 9.1%, wage mark-up shocks by 9.0%, and shocks to preferences by 1.8%. Contrarily, shocks to investment-specific technology are dampened by 6.5%, and government spending shocks by 2.5%. For all shocks, except for shocks to preferences, the CE and VE work in the same direction.[29] The shock-specific amplification is mainly driven by the CE, as for total amplification. Except for shocks to preferences, we find that all amplification measures are significantly different from 0 at the 5% level.

Next, we investigate the components of GDP. The results for consumption and investment are shown in the middle and lower panels of Table 7, respectively. For consumption, the amplification results are qualitatively the same as for GDP, except for shocks to preferences and government spending. However, the volatility differences across the models are much more pronounced. Over all shocks, the volatility in consumption is amplified by 18.7% in total. For the two most important shocks to consumption, i.e., labor productivity and wage mark-ups, the total volatility increase is given by 21.0% and 20.2%, respectively. Contrarily to GDP, consumption is positively correlated with the number of firms in the presence of a government spending shock, amplifying the crowding out in consumption. For consumption, all amplification measures are significantly different from 0 at the 5% level.

For total investment, the CE has two opposing effects. Recall that total investment is defined as the sum of investment in physical capital and investments in new firms. On the one hand, a lower price mark-up boosts GDP and therefore increases investment in physical capital for existing firms. On the other hand, a lower price mark-up reduces the incentive to invest into new firms. We find that the latter effect dominates such that an increase in the number of firms reduces total investment through the CE and outweighs the positive VE. Over all shocks, the volatility in total investment is dampened by −2.3%. However, we do not find this result to be significantly different from 0 at the 5% level.

7. ROBUSTNESS

In this section, we discuss several robustness checks for our estimation and amplification results. First, we re-estimate the translog model using a limited data sample until 1998. Second, we re-estimate the translog model using additional data on mark-ups and on profits. Finally, we estimate the two CES models and use these estimated models to quantify the amplification mechanism. Details on the results of our robustness exercises can be found in Supplementary Appendix B.2.

Subsample estimation. In the first exercise, we check whether the missing observations of firm entry in our data sample considerably affect our estimation and amplification results. We therefore re-estimate the model with translog preferences

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using only the limited sample period until 1998:Q2, which is the latest data point available for the new firm series. Hence, all missing observations are excluded from the data sample. Everything else remains the same.

Most parameter values are not significantly different from the parameter estimates of the full sample estimation.[30] Two differences are worth mentioning. First, the estimate of the labor share in production is given by 0.91, which is even higher than the estimate of 0.85 in the full sample estimation. However, in both estimations the values correspond roughly to the same labor share in GDP of about 70%. Second, the steady-state price mark-up is estimated at 1.43, which is substantially higher than the full sample estimate of 1.26. This implies stronger CE and VE in this sample period. The estimate of μ^p implies a point estimate for the CE ξ equal to 0.3 with a confidence band ranging from 0.24 to 0.35. The implied VE ω is estimated at 0.22 with a confidence band from 0.16 to 0.28. Due to the larger estimates for the CE and VE, the amplification measures are also substantially higher when compared to the baseline estimation. The overall amplification of GDP, consumption, and total investment through the CE and VE is now given by 10.3%, 24.4%, and −4.5%, respectively. These numbers are also significantly different from 0 at the 5% level.

Estimation using mark-up and profit data. Our analysis so far has shown that the CE, i.e., the effect of a change in the number of firms on mark-ups, is statistically significant and economically relevant. Therefore, one might argue that it is important to incorporate a measure of mark-ups in the estimation of the model. In our baseline estimation, we do not use a mark-up measure because mark-ups of prices over marginal costs are unobserved and the construction of a fully model-consistent mark-up measure is impossible.

Nevertheless, it is important to check whether our results are robust if we add a mark-up proxy to our data set. We construct two different proxies. The first one (denoted as mark-up data I) is based on the inverse labor share $Y_t/(w_t L_t)$. It is derived from the model's definition of the price mark-up that is given by $\mu_t^p = \alpha Y_t^c/(w_t L_t^c)$. Y_t^c is the aggregate output of final goods consumption, which does not include investments into new firms. L_t^c is the corresponding labor input. Since both Y_t^c and L_t^c are not observable, we use the gross domestic product Y_t and overall labor L_t for the construction of our proxy.[31]

Our second mark-up proxy (denoted as mark-up data II) is constructed from data on profits using the relation $N_t d_t = (1 - 1/\mu_t^p) Y_t^C$. This relation also contains the unobservable variable Y_t^c, which we again replace by Y_t. Moreover, it requires to use profit data that, as we argue below, suffers from a measurement problem as well.

To account for the differences between our proxies and the model-consistent definition of the mark-up, we include an error term $\varepsilon_t^{\mu,me}$ in the measurement equation, where $\varepsilon_t^{\mu,me}$ is assumed to be i.i.d.$N(0, \sigma^2_{\varepsilon^{d,me}})$. This also ensures that the model is not subject to stochastic singularity. The measurement equation for both

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proxies then reads as

$$l(\text{MARKUP}_t) = 100\hat{\mu}_t^p + \varepsilon_t^{\mu,me}\,. \tag{26}$$

The dynamics of firm entry are also strongly linked to firms' profits. Therefore, we also add the growth rate of real per capita corporate profits after taxes to our set of observables. We map this measure to overall profits that are defined by the number of firms N_t times the (real) average profits per firm d_t^r. Note, though, that profits in the model are economics profits, whereas in the data profits are accounting profits. One of the main differences is that accounting profits still contain costs of capital since parts of the capital stock are equity-financed. Contrarily in the model, capital costs are fully subtracted out. To account for the difference between profits in the data and in the model, we include the measurement error $\varepsilon_t^{d,me}$ in the measurement equation, where $\varepsilon_t^{d,me}$ is assumed to be i.i.d.$N(0, \sigma^2_{\varepsilon^{d,me}})$. The measurement equation for profits then reads as

$$dl(\text{PROFITS}_t) = 100(\Delta\hat{d}_t^r + \Delta\hat{N}_t) + \varepsilon_t^{d,me} \tag{27}$$

We re-estimate the baseline model using additionally mark-up data I, mark-up data II or data on profits.[32] Using the inverse labor share as proxy (mark-up data I), the steady-state price mark-up is estimated at 1.19 which is lower than the baseline estimate of 1.26. As a result, the total amplification effect on output amounts to 6.9%, which is lower than the baseline estimate of 8.5% but still significantly greater than 0. The results of the remaining two estimates are even closer to our baseline estimates. The total amplification on output is given by 7.9% using mark-up data II and 8.8% using profit data. In summary, we only find small and insignificant differences in the structural parameter estimates and the amplification measures to our baseline estimates if we include data on price mark-ups or profits to our set of observables.[33] The estimated models are able to capture the procyclicality of profits and the countercyclicality of mark-ups in the data. However, a large fraction of the variations in the mark-up and profit data is captured by the measurement errors.[34] We argue that this is at least partly due to the model-inconsistent construction of the mark-up data and the described differences in the concept of profits between data and model.

Estimation of CES models. In the preceding section, we have used the same estimated parameter set in all three model frameworks in order to isolate the model-specific CE and VE that exclusively result from the different model setups. In this last exercise, we estimate the two CES models using the same data set as in our baseline estimation of the translog model. The constant price mark-up is fixed to the estimated steady-state value under the translog specification. In a second step, we compute the amplification measures using the two estimated CES models and the estimated translog model.

The parameter estimates of the CES models are not significantly different from the parameter estimates of the translog model.[35] All estimates lie within the 90% probability interval of the translog estimation. Using the estimated CES models, we therefore obtain similar amplification measures. For the two most important shocks to GDP, i.e., labor productivity and wage mark-ups, the total amplification amounts to 8.7% and 13.2%, respectively. Note that we do not give overall amplification measures and probability bands. Since we estimate different shocks processes across models, differences in the absolute standard deviations do not show the strength of the amplification mechanism but rather reflect the ability of the models to capture the volatility in the data. On the contrary, shock-specific amplification measures are computed in relative terms and thus control for the different estimates of the shock processes. The computation of the corresponding probability bands would require to know the joint posterior distribution under the translog and the CES models.

8. CONCLUSION

This paper studies the empirical importance of endogenous firm entry as amplification mechanism for business cycle fluctuations. To this end, we use the firm entry model by Bilbiie et al. (2012), extend it with several real frictions and estimate the model on U.S. data with Bayesian methods. In this model, the amplification mechanism of firm entry works through a CE and a VE. Both effects are estimated to be statistically significant.

To quantify the strength of this amplification mechanism and to disentangle the CE and VE, we also specify two model frameworks, where either the CE or both effects are switched off. We measure the amplification as the percentage volatility difference in GDP, consumption, and investment across the three model variants.

Our results support the findings of Jaimovich and Floetotto (2008) that endogenous firm entry is an important amplification mechanism for business cycle fluctuations. However, in a medium-scale environment—as considered here—the quantitative impact of firm entry is less dominant. Over all shocks, the CE and VE substantially amplify GDP by 8.5%. The impacts of the CE and VE are shock dependent. For labor productivity and wage mark-up shocks, the CE and VE amplify the impacts on GDP, but dampen the impacts of shocks to aggregate demand and to investment-specific technology. The CE accounts for most amplification, whereas the VE only plays a minor role.

In the theoretical framework each firm produces one differentiated product, i.e., we have an identity between the number of firms and products. In our empirical exercise, we exclusively focus on firm entry dynamics by using data on NBI. However, this approach neglects the effect of product creation at existing firms. Bernard et al. (2010) and Broda and Weinstein (2010) highlight the empirical importance of product creation in business cycle fluctuations. We leave it to future research to identify the entry mechanism with data on product creation.

NOTES

1. See, e.g. Smets and Wouters (2007) and Christiano et al. (2005).

2. The empirical evidence is based on U.S. data. The procyclicality of firm entry is demonstrated by Chatterjee and Cooper (2014), Devereux et al. (1996), or Etro and Colcagio (2010). Davis et al. (1998) investigate the role of firm turnover for job flows. Bernard et al. (2010) compute the contribution of product creation for aggregate output.

3. For a detailed overview on the existing literature, see Bilbiie et al. (2012, Section 5).

4. Note that this effect is equivalent to the well-known love of VE, where households "love" varieties and gain utility from an increasing set of consumption goods.

5. Note that Bilbiie et al. (2012) aggregate products through the consumers' intratemporal optimization and therefore refer to a translog expenditure function instead. However, both concepts are equivalent.

6. We show in a robustness exercise that all our results go through when we include a mark-up proxy in the estimation.

7. The main difference in terms of modeling strategy is that we consider a flexible-price (real business cycle) model with endogenous entry, whereas Lewis and Stevens (2015) consider a sticky-price (New Keynesian) endogenous entry model. In this sense, the papers complement each other by providing evidence on the parameter governing the CE on the grounds of different model classes. Note that the estimates of the parameter governing the CE are not very different across the two papers. Together with the fact that the basic transmission mechanism through which firm entry amplifies output dynamics do not differ in a flexible-price versus sticky-price model, this suggests that the amplification effect on output is invariant to introducing nominal rigidities. To confirm this, a comprehensive quantitative assessment of the amplification mechanism on output within a sticky-price model is required. We leave this for future work.

8. Other studies that consider a supply-side-driven CE in business cycle models are, for example, Colcagio and Etro (2010), Etro and Colcagio (2010), and Colciago and Rossi (2015). In contrast to Jaimovich and Floetotto (2008), however, these studies do not provide a quantitative evaluation of the amplification mechanism.

9. The structure of our core model is based on Schmitt-Grohé and Uribe (2012). They estimate the model to assess the contribution of news shocks to business cycle fluctuations.

10. See Supplementary Appendix A.1 for the derivation of the price index P_t and the price elasticity ε_t. For convenience, we denote N_t in the following as the number of firms/varieties. Note, however, that $N_t \in \mathbb{R}$ is strictly speaking the mass of firms.

11. The moving average term allows the wage mark-up shock to capture high frequency movements in the wage series, see Smets and Wouters (2007).

12. Empirically, firm entry lags GDP. See, for example, Devereux et al. (1996).

13. Recall that, in the steady state of the translog model, $\xi = \frac{1}{1+\tilde{\sigma}N}$, $\omega = \frac{1}{2\tilde{\sigma}N}$, and the price mark-up is given by $\mu^p = 1 + \frac{1}{\tilde{\sigma}N}$.

14. See Supplementary Appendix A.2 for the model equations and derivations of the final goods production sector under the CES specifications.

15. The log-linearized model equations are summarized in Supplementary Appendix A.3.

16. Recall that in our model GDP, Y_t is the sum of output of final goods Y_t^C plus investment into new firms. For the sake of convenience, we use from now on the simple term output to refer to Y_t.

17. Alternatively, one can use the data series net business formation (NBF) published in the same survey as measure for net firm entry. We decided to use the NBI measure for two reasons: First, data on NBF are only available until 1995:Q3, whereas NBI is published until 1998:Q3. Second, we do not model firm exit endogenously. We, therefore, believe that NBI is a closer measure for firm entry than NBF for net firm entry.

18. Note that the missing observations of the new firm series are treated as an unobserved state during the Kalman filter routine. We show in a robustness exercise in Section 7 that our estimation results do not change substantially if we limit our data sample to 1998:Q3.

19. Note that we use the data-consistent measures of real variables to map the data with the model, see also Section 2.5.

20. The concept to capture the common movement of multiple time series in a few latent variables originally comes from the factor analysis. For a general discussion of estimating DSGE models in a date-rich environment, see Boivin and Giannoni (2006).

21. From the estimated value of μ^p together with the implied value of $\tilde{\sigma} = 2.21$, we can deduce the steady-state mass of firms using $\mu^p = 1 + \frac{1}{\tilde{\sigma} N}$. This delivers $N = 1.74$. This value, together with other estimates, implies a steady-state share of entry costs in GDP equal to 12.81%, which is in line with the estimates of Barseghyan and DiCecio (2011).

22. A re-estimated model using an AR(2) process for the entry cost shock performs better in fitting the persistence of firm entry growth. However, the overestimation of the entry growth volatility is even stronger under this specification.

23. We also re-estimate the model using data on consumption and investment as defined in Smets and Wouters (2007). In line with Justiniano et al. (2010), we find that the importance of the investment-specific technology shock in fact becomes smaller under this specification, explaining only 1.5% of the variations in GDP. Details on the estimation are available upon request.

24. To further explore this argument, we re-estimate a version of our model in which firm entry is switched off (we achieve this by fixing the parameter governing the firm entry adjustment costs at $\kappa_E = 1000$ and exclude firm entry data from our set of observables). In fact, we find that this leads to an increase in the importance of investment-specific technology shocks, explaining 9.3% of the variations in GDP.

25. Note that shocks to entry costs induce a procyclical movement of the number of firms in the translog model. However, entry costs shocks lead to qualitative different output responses across the three models. We, therefore, exclude this shock from our amplification analysis. Including this shock would only slightly change the overall amplification results discussed in Section 6.2.

26. A detailed exploration of government spending shocks in models with endogenous entry is provided by Lewis and Winkler (in press). Cardi and Restout (2015) and Lewis and Winkler (2015) analyze fiscal policy in open-economy endogenous entry models.

27. This ensures that we extract the model-specific amplification effect that exclusively results from the different model setups. In a robustness exercise in Section 7, we estimate both CES models separately and obtain similar amplification results using the estimated CES models.

28. As in the preceding section, GDP is deflated by the relative price ρ_t.

29. Note that the VE on data-consistent variables, as considered here, is smaller than for welfare-consistent variables since $\partial \hat{Y}_t^r / \partial \hat{\rho}_t = \partial \hat{Y}_t / \partial \hat{\rho}_t - 1$ and $\partial \hat{Y}_t / \partial \hat{\rho}_t > 0$. Except for shocks to preferences, the effect through Y_t dominates the effect that stems from deflating.

30. Details on the estimation and amplification results are given in Tables B.1 and B.2 in Supplementary Appendix B.2.

31. More details on the construction of our mark-up and profit series can be found in the data appendix.

32. Details on the estimation and amplification results are given in Tables B.1 and B.3–B.5 in Supplementary Appendix B.2.

33. Note that this also holds when we use growth rates (instead of log-levels) of the mark-up proxies. Details on the estimations are available upon request.

34. This confirms the profit volatility puzzle, i.e., the inability of standard business cycle models to account for the volatility of profits. See, e.g., Lewis and Stevens (2013) or Etro and Colcagio (2010).

35. Details on the estimation and amplification results are given in Tables B.6 and B.7 in Supplementary Appendix B.2.

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APPENDIX

A. DATA APPENDIX

TABLE A.1. Data sources

Series ID	Description	Source
GDPC96	Real gross domestic product	BEA
GDP	(Nominal) gross domestic product	BEA
PCND	Personal consumption expenditures: non-durable goods	BEA
PCESV	Personal consumption expenditures: services	BEA
PCDG	Personal consumption expenditures: durable goods	BEA
FPI	Fixed private investment	BEA
CBI	Change in private inventories	BEA
PRS85006033	Non-farm business hours worked index (2005=100)	BLS
PRS85006103	Non-farm business hourly compensation index (2005=100)	BLS
CES0500000008	Average hourly earnings of production	BLS
NBI	New business incorporations	SCB from BEA
CNP160V	Civilian noninstitutional population	BLS
GDPDEF	Gross domestic product: implicit price deflator	BEA
CPATAX	Corporate profits after tax with IVA and CCAdj	BEA

Notes: BEA: U.S. Bureau of Economic Analysis, BLS: U.S. Bureau of Labor Statistics, SCB: Survey of Current Businesses. Data series on profits are used in the robustness checks.

TABLE A.2. Construction of data series

Time series		Construction	Description
$dl(\text{GDP}_t)$	$=$	$dl\left(\dfrac{\text{GDPC96}_t}{\text{CNP160}V_t}\right)$	Growth rate of real per capita GDP
$dl(\text{CONS}_t)$	$=$	$dl\left(\dfrac{\text{PCND}_t + \text{PCESV}_t}{\text{CNP160}V_t \times \text{GDPDEF}_t}\right)$	Growth rate of real per capita consumption
$dl(\text{INV}_t)$	$=$	$dl\left(\dfrac{\text{FPI}_t + \text{PCDG}_t + \text{CBI}_t}{\text{CNP160}V_t \times \text{GDPDEF}_t}\right)$	Growth rate of real per capita investment
$dl(\text{WAGE1}_t)$	$=$	$dl\left(\dfrac{\text{PRS85006103}_t}{\text{GDPDEF}_t}\right)$	Growth rate of first measure of real wage
$dl(\text{WAGE2}_t)$	$=$	$dl\left(\dfrac{\text{CES0500000008}_t}{\text{GDPDEF}_t}\right)$	Growth rate of second measure real wage
$l(\text{HOURS}_t)$	$=$	$l\left(\dfrac{\text{PRS85006033}_t}{\text{CNP160}V_t}\right)$	Logarithm of per capita hours worked
$dl(\text{ENTRY}_t)$	$=$	$dl\left(\dfrac{\text{NBI}_t}{\text{CNP160}V_t}\right)$	Growth rate of per capita new firms
$dl(\text{PROFITS}_t)$	$=$	$dl\left(\dfrac{\text{CPATAX}_t}{\text{CNP160}V_t \times \text{GDPDEF}_t}\right)$	Growth rate of real per capita profits
$l(\text{MARKUP1}_t)$	$=$	$l\left(\dfrac{\text{GDPC96}_t \times \text{GDPDEF}_t}{\text{PRS85006103}_t \times \text{PRS85006033}_t}\right)$	Logarithm of mark-up measure I
$l(\text{MARKUP2}_t)$	$=$	$l\left(\left[1 - \dfrac{\text{CPATAX}_t}{\text{GDP}_t}\right]^{-1}\right)$	Logarithm of mark-up measure II

Notes: The function l and dl stand for 100 times the demeaned logarithm and the demeaned log-difference, respectively. Data series on profits and mark-ups are used in the robustness checks.

B. SUPPLEMENTARY MATERIAL

The Supplementary Appendix is available online at the corresponding authors' website: `https://sites.google.com/site/rolandcwinkler`.

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