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endogenous firm entry in an estimated model of the U.S. business cycle - updated version -

by Sven Offick and Roland C. Winkler

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Endogenous Firm Entry in an Estimated Model of the U.S. Business Cycle*

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Abstract

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 and the variety effect. This paper tests the significance of this amplification mechanism, quantifies its importance, and disentangles the competition and the variety effect. To this end, we estimate a medium-scale real business cycle model with firm entry for the U.S. economy. The competition and the variety effect are estimated to be statistically significant. Together, they amplify the volatility of output by 8.5 percent relative to a model in which both effects are switched off. The competition effect accounts for most amplification, whereas the variety effect only plays a minor role.

JEL classification: E20, E32

Keywords: Bayesian estimation, Business Cycles, Competition Effect, Entry, Mark-ups, Variety Effect

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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 percent of quarterly job gains. Third, product creation (at new and existing firms) accounts for almost 50 percent 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 fluctuations.³ This literature identifies endogenous entry as an important amplification mechanism for business cycle fluctuations. This amplification mechanism works through two channels. The variety effect describes the productivity gains from additional varieties. An increase in the number of firms, equivalent to an increase in the number of varieties, increases output more than proportional due to increasing returns to specialization.⁴ The so-called competition effect captures the inverse relation between the number of producers and price mark-ups. An increase in the number of producers erodes market power. Price mark-ups fall which in turn boosts aggregate demand.

This paper aims to test the significance of this amplification mechanism, to quantify its importance, and to disentangle the competition and the variety effect in a medium-scale business cycle model. To this end, we use the firm entry model by Bilbiie, Ghironi, and Melitz (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

¹See e.g. Smets and Wouters (2007) and Christiano, Eichenbaum, and Evans (2005).

²The empirical evidence is based on US data. The procyclicality of firm entry is demonstrated by Chatterjee and Cooper (1993), Devereux, Head, and Lapham (1996), or Etro and Colcagio (2010). Davis, Haltiwanger, and Schuh (1998) investigate the role of firm turnover for job flows. Bernard, Redding, and Schott (2010) compute the contribution of product creation for aggregate output.

³For a detailed overview on the existing literature, see Section 5 in Bilbiie, Ghironi, and Melitz (2012).

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

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

condition that equates expected future profits with entry costs. Under the translog technology both the competition and the variety effect are present. The competition effect 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 competition effect and the variety effect to be statistically significant. To quantify the strength of the amplification mechanism and to disentangle the competition and the variety effect, we specify two counterfactual model frameworks with a constant elasticity of substitution (CES) production technology, where either the competition effect 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. By conducting counterfactual simulations, we find that the competition and variety effect substantially amplify fluctuations in output and consumption, but dampen fluctuations in investment. For output, the total increase in volatility is given by 8.5 percent. The competition effect accounts for most of the amplification, amplifying output by 7 percent, whereas the increase through the variety effect only amounts to 1.5 percent. If we consider each structural shock in isolation, the results are mixed. On the one hand, competition and variety effect amplify the impacts of labor productivity and wage mark-up shocks on output. This follows from the fact that for these shocks, output and firm entry are positively correlated. On the other hand, the competition and variety effect dampen the output effects of aggregate demand and investment-specific technology shocks, for which the conditional correlation between firm entry and output is negative.

The evidence on the cyclicity 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) and Rotemberg and Woodford (1999), while 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 Colcagio and Etro (2010) and Lewis and Poilly (2012). However, mark-ups are not directly unobservable. 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 cyclicity 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

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

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. Lewis and Stevens (2015) estimate – as we do – a business cycle with firm entry using Bayesian methods. However, they consider a monetary DSGE model and focus mainly on the role of firm entry for inflation dynamics. Our primary focus is on output dynamics and on the amplification mechanism embedded in the endogenous entry model.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 amplification effect associated with firm entry amplifies the impacts of technology shocks on output by 64 to 158 percent, 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 variety effect is turned off, and the sole focus lies on the competition effect. 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 competition effect. Therefore, we consider a demand-side driven competition effect 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 competition and the variety effects have on the model's dynamics. Section 4 describes the data and the estimation procedure. Section 5 discusses the

⁷We consider a real model. While the transmission channels through which firm entry affects the model dynamics (the competition and variety effect) would also be at work in a sticky-price framework, the quantitative results may change. We leave a quantitative evaluation within a sticky-price model for future work.

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

estimation results. Section 6 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 which 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, Ghironi, and Melitz (2012) which features a variety effect and a demand-side driven competition effect 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 intermedi-

⁹The 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.

ate 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 $P_t = \exp\left(\frac{(\tilde{N} - N_t)}{(2\tilde{\sigma}\tilde{N}N_t)}\right) p_t$, 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 variety effect), 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

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

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 :

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

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

¹⁰See Appendix A 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.

decreasing in the number of goods. The competition effect 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

$$w_t = \alpha m c_t \frac{y_{i,t}}{l_{i,t}}, \quad (3)$$

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

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 $L_t = \left(\int_0^1 L_{j,t}^{1/\mu_t^w} dj \right)^{\mu_t^w}$. 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

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

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

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

2.4 Households

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

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

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.* $N(0, \sigma_{\varepsilon^\chi}^2)$. S_t is a habit-adjusted weighted average of current and past consumption, which evolves over time according to

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

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

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

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.* $N(0, \sigma_{\varepsilon^{f_E}}^2)$. 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 $(1 - \delta)(v_t + d_t) \left(1 - \frac{\kappa_E}{2} \left(\frac{N_{E,j,t-1}}{N_{E,j,t-2}} - 1\right)^2\right) N_{E,j,t-1}$. 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

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

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 $K_{j,t}^s = u_{j,t} K_{j,t}$. We assume that an increasing utilization of capital implies a higher depreciation rate $\delta^K(u_{j,t})$, specified as

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

where δ_0 is the capital depreciation 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), (8), (9), (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 $\lambda_t^C, \lambda_t^C Q_t, \lambda_t^S$ denote Lagrange multipliers for the budget constraint, the capital accumulation

¹²Empirically, firm entry lags GDP. See, for example, Devereux, Head, and Lapham (1996).

equation, and the definition of S_t , respectively. The first-order conditions read as follows:

$$\lambda_t^C = \beta R_t \mathbf{E}_t \{ \lambda_{t+1}^C \} , \quad (11)$$

$$\lambda_t^C Q_t = \beta \mathbf{E}_t \{ \lambda_{t+1}^C (r_{t+1}^K u_{t+1} + Q_{t+1} (1 - \delta^K (u_{t+1}))) \} , \quad (12)$$

$$\lambda_t^C v_t = (1 - \delta) \beta \mathbf{E}_t \{ \lambda_{t+1}^C (v_{t+1} + d_{t+1}) \} , \quad (13)$$

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

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

$$1 = Q_t u_t^I \left(1 - \frac{\kappa_I}{2} \left(\frac{I_t}{I_{t-1}} - 1 \right)^2 - \kappa_I \left(\frac{I_t}{I_{t-1}} - 1 \right) \frac{I_t}{I_{t-1}} \right) + \beta \mathbf{E}_t \left\{ \frac{\lambda_{t+1}^C}{\lambda_t^C} Q_{t+1} u_{t+1}^I \kappa \left(\frac{I_{t+1}}{I_t} - 1 \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right\} , \quad (16)$$

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

$$r_t^k = Q_t (\delta_1 + \delta_2 (u_t - 1)) , \quad (18)$$

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

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

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

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

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

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 $\frac{\kappa_E}{2} \left(\frac{N_{E,t-1}}{N_{E,t-2}} - 1 \right)^2$.

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 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 model. In the translog model, the competition effect ξ and the variety effect 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 the following, we introduce two alternative model specifications that use a constant elasticity of substitution (CES) production function for final goods as in Benassy (1996) which is characterized by constant price mark-ups (and therefore does not feature a competition effect, $\xi = 0$) and that allows to freely parameterize the variety effect.¹⁴ In the first CES specification, the variety effect 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 variety effect is set equal to zero, i.e. $\omega = 0$. We denote this the CES-NoVE model. Table 1 summarizes the competition and variety effect in all three model variants, in each case evaluated at the deterministic steady state. In all other respects, the models are identical.

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

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

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	$\xi = 0$	$\omega = 0$

In the following, we estimate the competition and variety effect. 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 competition and variety effect in amplifying business cycle fluctuations and to disentangle competition and variety effect 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 competition and variety effect in terms of amplifying business cycle fluctuations, it is instructive to examine the analytics and the intuition of the amplification mechanism in our model. To this end, we consider a simplified version of our baseline model which allows us to provide analytical results. For illustration purposes, we limit our analytical 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

¹⁵The log-linearized model equations are summarized in Appendix B.

Table 2: Linearized model equations in simplified model variant

$\hat{w}_t = (\eta - 1)\hat{L}_t$	Labor supply
$\hat{w}_t = \hat{z}_t + \hat{\rho}_t - \hat{\mu}_t$	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

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 effects the competition and variety on the dynamics of employment, consumption and output after a rise in labor productivity \hat{z}_t . Combining labor supply with labor demand to substitute out the real wage, replacing $\hat{\mu}_t^p$ from the definition of the competition effect and $\hat{\rho}_t$ from the definition of the variety effects yields the following equation for aggregate employment:

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

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 competition effect and/or the variety effect 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 $\hat{C}_t^r = \hat{C}_t - \hat{\rho}_t$ is given by

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

Combining the definition of GDP with the aggregate resource constraint and the equation for

aggregate profits, replacing $\hat{\mu}_t^p$ from the definition of the competition effect, and inserting the equation for \hat{C}_t from above yields $\hat{Y}_t = \omega\eta/(\eta - 1)\hat{N}_t + (2\eta(\mu^p - 1) + 1)/((\eta - 1)(2\mu^p - 1))\xi\hat{N}_t + \eta/(\eta - 1)\hat{z}_t$, or in data-consistent terms

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

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

The amplification mechanism is evident from equations (22), (23), and (24). To see this, consider a positive innovation to labor productivity, i.e. $\hat{z}_t > 0$, and suppose that the number of firms increases after a rise in productivity, i.e. $\partial\hat{N}_t/\partial\hat{z}_t > 0$. If this happens, the effects of a rise in labor productivity on employment, consumption and output are amplified in the presence of the competition and/or variety effect, i.e. if $\xi > 0$ and/or $\omega > 0$. The stronger the competition and/or variety effect, the more does economic activity rise after a positive innovation to productivity. The rationale is that in the presence of the variety effect, an increase in the number of firms increases output more than proportional due to increasing returns to specialization. In the presence of the competition effect, an increase in the number of producers erodes market power. Price mark-ups fall which in turn boosts aggregate demand.

Notice, though, that the response of the number of firms to a labor productivity shock is ambiguous. If the number of firms drops, the effects of the productivity shock are dampened. Whether the number of firms rises or drops in response to a technology improvement is obviously an empirical question that we will address in the next section using our estimated baseline model. Moreover, our estimates will reveal whether ξ and ω are significantly different from zero and will allow us to quantify the strength of the competition and variety effect in amplifying or attenuating shocks to the economy.

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.¹⁶ 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, Primiceri, and Tambalotti (2013) and Gali, Smets, and Wouters (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 Appendix B. The data sample starts in 1964:Q1 and ends in 2012:Q2. Due to limited data availability, the new firm series ends in 1998:Q3.¹⁷

The measurement equations for GDP, consumption, investment, hours worked, and entry then read as follows:¹⁸

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

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:

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

where λ denotes the loading coefficient for the second wage series. Since both loadings are not

¹⁶Alternatively, 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 is 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.

¹⁷Note 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.

¹⁸Note that we use the data-consistent measures of real variables to map the data with the model, see also Section 2.5.

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

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 $i.i.d.N(0, \sigma_{\varepsilon^{w1,me}}^2)$ and $i.i.d.N(0, \sigma_{\varepsilon^{w2,me}}^2)$, 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.¹⁹

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 ε_t^{fE} , to preferences ε_t^X , 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 percent. 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 (2012), 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, Ghironi, and Melitz (2012). The steady-state values G/Y and L are set to 0.18 and 0.25, respectively. Following Gali, Smets, and Wouters (2012), we set the steady-state wage mark-up μ^w at 20 percent.

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 are assumed to follow an inverse gamma distribution with mean 0.02 and standard deviation 1. For the autocorrelation parameters of the exogenous

¹⁹The 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).

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 zero 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 percent 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. Finally, we analyze the model-implied impulse responses to the structural shocks.

5.1 Parameter estimates

Table 4 displays the estimated parameters as means of the posterior distribution and the 90 percent 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 percent with a probability band ranging from 16 percent to 36 percent. 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 competition and the variety effect, the point estimate of μ^p implies that a one percent increase in the mass of firms lowers the price mark-up by 0.21 percent (the competition effect ξ) and raises the relative price by 0.13 percent (the variety effect ω). Competition and variety effect are statistically significantly different from zero with confidence bands for ξ and ω ranging from 1.14 to 1.26 and 0.08 to 0.18, respectively.

Table 4: Results from the Bayesian estimation including prior distribution and probability intervals

Parameter	Prior distribution			Posterior distribution		
	Type	Mean	Std	Mean	[5% , 95%]	
<i>Structural parameters</i>						
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 elast. 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 adj. cost	κ_I	Gamma	4.0	1.0	3.82	[2.59 , 5.28]
Inv. elast. of capital util.	$\frac{\delta_2}{\delta_1}$	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 adj. cost	κ_E	Gamma	4.0	1.0	1.50	[1.09 , 1.99]
<i>Autocorrelation of shock processes</i>						
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]
Invest. spec. tech.	ρ_I	Beta	0.5	0.2	0.24	[0.12 , 0.38]
Gov. 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]
<i>Standard deviation of innovations</i>						
Labor prod.	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]
Invest. spec. tech.	σ_{ε^I}	Igamma	2.0	1	3.99	[2.39 , 6.54]
Preference	σ_{ε^x}	Igamma	2.0	1	1.46	[1.07 , 1.91]
Gov. 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]
<i>Moving average parameter and loading coefficient</i>						
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]

Note: Using a Random Walk Metropolis Hastings algorithm, we generate 2 chains of 2 Mio. 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.

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, Plosser, and Rebelo (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. Notice 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 percent.

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 cor-

Table 5: Second moments

	X	Std (σ_X)			1st-order autocorr.		
		Data	Model		Data	Model	
			Mean	[5% , 95%]		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	$\Delta\hat{T}I^r$	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]

	X	Rel. std. ($\sigma_X/\sigma_{\Delta\hat{Y}^r}$)			Contemp. $corr(X, \Delta\hat{Y}^r)$		
		Data	Model		Data	Model	
			Mean	[5% , 95%]		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	$\Delta\hat{T}I^r$	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]

Note: 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.

relations 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 .²⁰

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

²⁰A 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.

Table 6: Variance decomposition at business cycle frequency

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

Note: Main figures are computed at the posterior mean reported in Table 4. Figures in brackets give the corresponding fifth and ninety fifth 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 to 32 and take the mean. Shares may not add up to 100 due to rounding.

they account for more than 75 percent of the variations in GDP, consumption, total investment, hours worked, and wages. The investment-specific technology shock explains 21 percent 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, Primiceri, and Tambalotti (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, Primiceri, and Tambalotti (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, Primiceri, and Tambalotti (2010).²¹

We argue that the difference in the importance of the investment-specific technology shock is (at

²¹We also re-estimate the model using data on consumption and investment as defined in Smets and Wouters (2007). In line with Justiniano, Primiceri, and Tambalotti (2010), we find that the importance of the investment-specific technology shock in fact becomes smaller under this specification, explaining only 1.5 percent of the variations in GDP. Details on the estimation are available upon request.

least partly) due to the endogenous firm entry mechanism which 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 the positive comovement 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.²²

5.3 Impulse responses

In this section, we analyze the model-implied impulse responses to the various structural shocks. The aim of this section is to illustrate the amplification mechanism and to visualize the impact of the competition and variety effect on the model dynamics. To this end, we present the impulse responses for three models, the estimated translog model and two counterfactuals: the CES-TrVE model with the competition effect switched off and the CES-NoVE model with competition and variety effect switched off. For both CES models, we keep the parameter estimates from the translog model.

Figure 1 to 6 show 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 the six structural shocks. All real variables are shown using the data-consistent deflator p_t . Impulse responses are measured as percentage deviations from steady states. The shaded areas are the 90 percent probability bands which reflect parameter uncertainty in the translog model.

To start with, Figure 1 plots the responses to a positive labor-augmenting technology shock z_t . This boosts 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 competition effect, this makes products closer substitutes and thus deteriorates market power in the monopolistic sector.

²²To 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 percent of the variations in GDP.

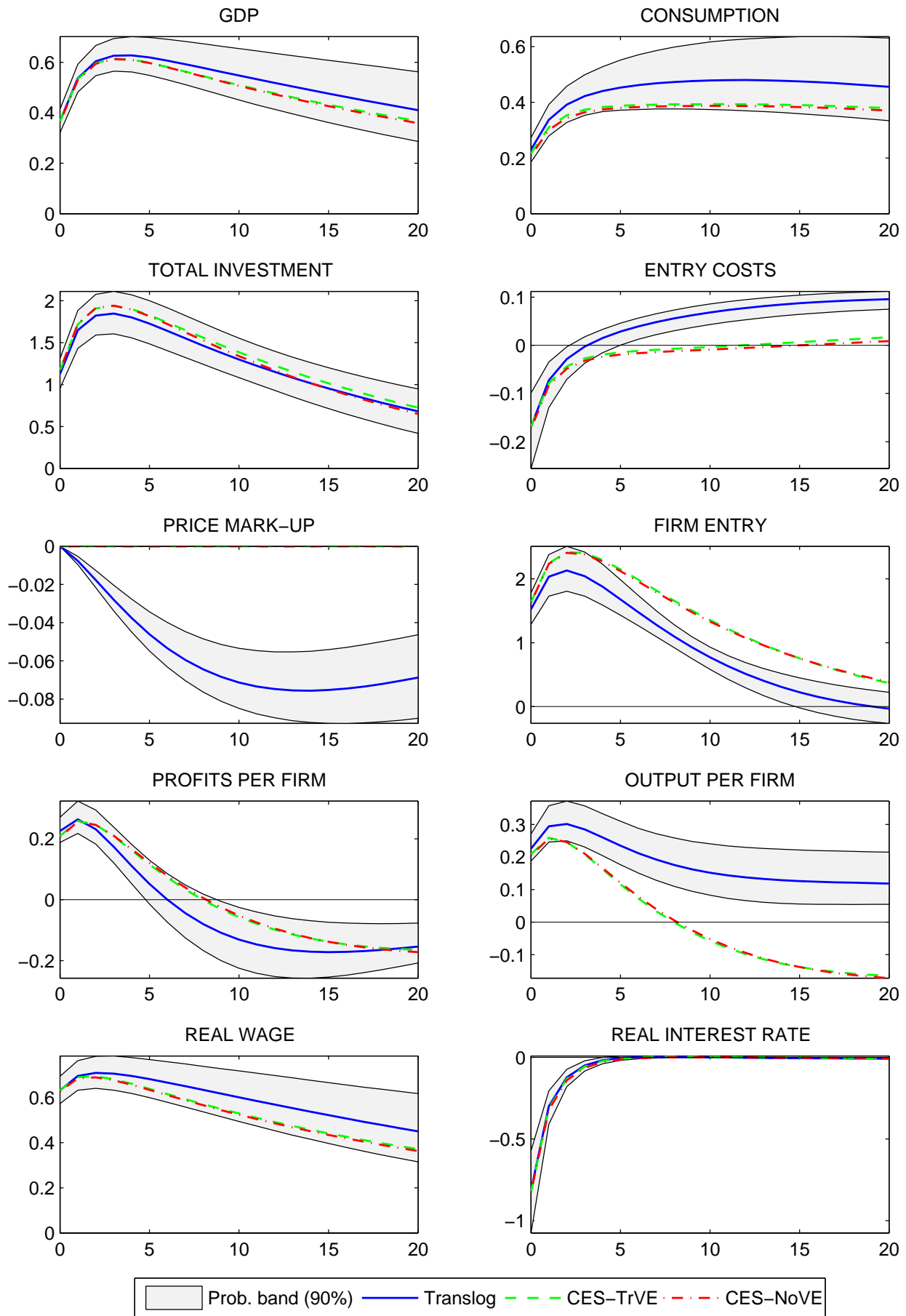


Figure 1: Impulse responses to a labor productivity shock

This leads to a decrease in price mark-ups, which boosts aggregate demand and induces individual firms to increase their production. The increase in aggregate demand is enforced by the drop in the welfare-relevant price index if the variety effect is present.

The magnification effect is evident in the impulse response functions. The competition effect and to a much lesser extent the variety effect 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 the Section 6.

Figure 2 shows the responses to an increase in wage mark-ups μ_t^w . The increase in wage mark-ups leads to a decline of GDP, consumption, and total investment. The drop in GDP and consumption is amplified when the competition and variety effect are at work. The reason is that firm entry is depressed by the increase in entry costs and the drop in firm profits triggered by the initial increase in real wages. Since the mass of firms declines, the product space becomes less crowded and the elasticity of substitution declines. Consequently, the price mark-up rises, which causes aggregate demand and individual firm's production to fall. In addition to the competition effect, the rise in the welfare-relevant price index (the variety effect) puts downward pressure on aggregate demand, although this effect seems to be quantitatively small. As in the case of labor productivity shocks, there is a dampening of the response of total investment when competition and variety effect are present.

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

The results are different when we consider shocks to investment-specific technology, to preferences, and to government spending. The reason is that the estimated conditional correlation between GDP and firm entry (or the number of firms) is negative for those shocks. Hence, compe-

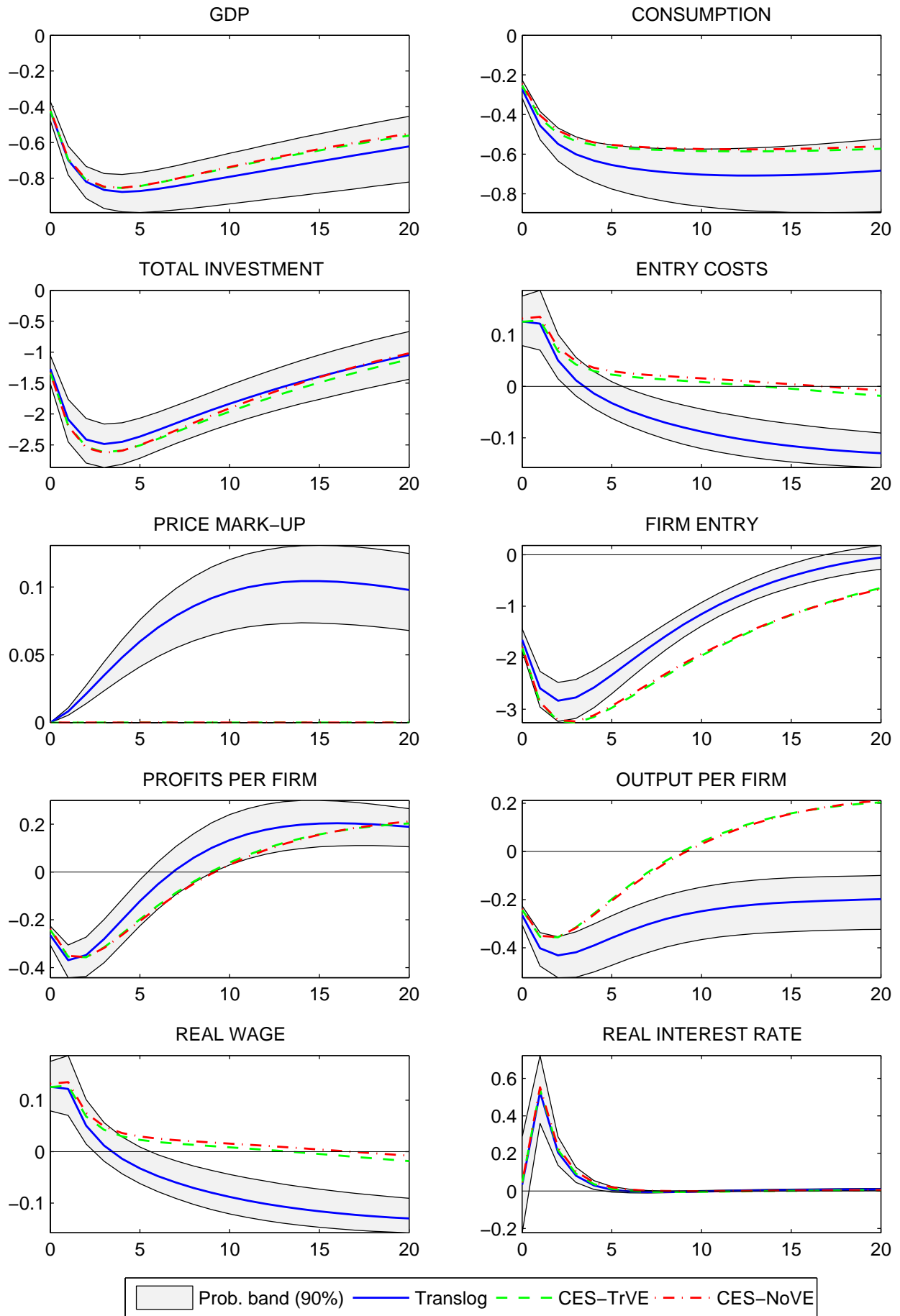


Figure 2: Impulse responses to a wage mark-up shock

tition and variety effect dampen the rise in GDP following positive shocks to investment-specific technology, preferences, and government spending.

Figure 3 shows the responses to the investment-specific technology shock u_t^I . The 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, firm entry falls inducing an increase in price mark-ups. The procyclical response of firm's market power abates the impacts of investment-specific technology shocks on GDP and consumption. The response of total investment is almost identical across the models.

Figures 4 and 5 show the responses to a preference shock χ_t that induces households to consume more and to a rise in government spending G_t , respectively. Both shocks raise aggregate demand and the real interest rate. The latter lowers firm values, which induces, in conjunction with the rise in entry costs, a decline in firm entry. Consequently, under translog preferences price mark-ups and the welfare-relevant price index rise, which both dampen the impacts of these aggregate demand disturbances on GDP.

Following a time-impatience shock, the responses of GDP, investment, and consumption are, however, not very different across the models. This is because the mark-up is only marginally affected by this type of shock. In contrast, the competition and variety effect visibly amplify the crowding-out of private consumption after a fiscal expansion, as can be seen from Figure 5. Private consumption falls due to the negative wealth effect of higher taxes and the rise in real interest rates. Investment is again only marginally affected by these mechanisms.

Finally, Figure 6 shows that an exogenous increase in entry costs $f_{E,t}$ generates a strong decline in firm entry. Households that invest less in new firms raise consumption and capital investment, at least on impact. The decrease in the number of products leads to an increase in the market power of firms when the competition effect is present. The increase in price mark-ups induces a fall in capital investment and consumption (in the medium run). GDP, after a temporary rise on impact, declines substantially. In the absence of the competition effect, the decline in GDP is only short-lived and followed by a hump-shaped rise. This can be explained by the significant increase of consumption, which is otherwise depressed by the sharp increase in price mark-ups. As in the case of shocks to investment-specific technology, to preferences, and to government spending, the increase in firm's market power lowers GDP. In the case of these disturbances the increase in GDP

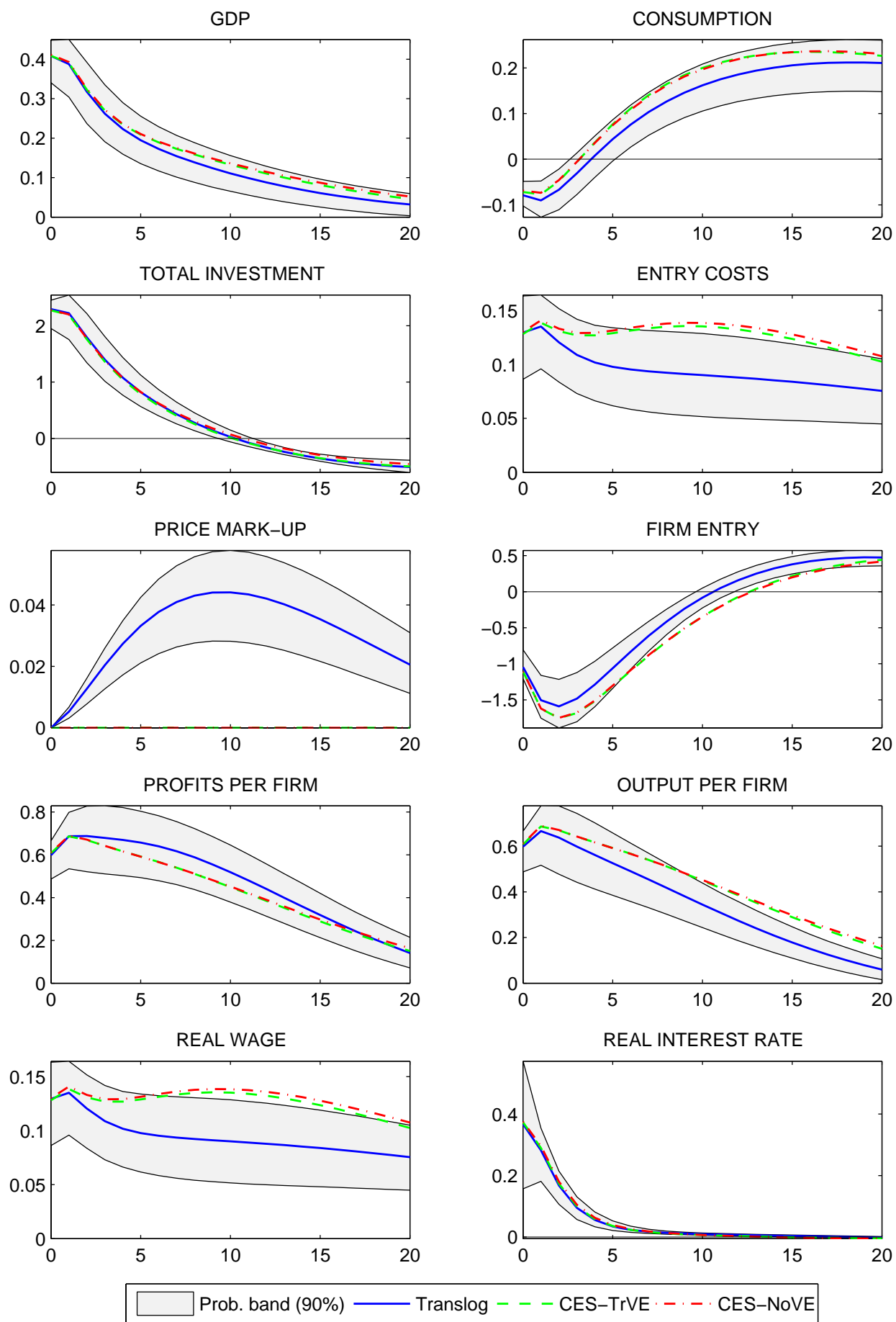


Figure 3: Impulse responses to an investment-specific technology shock

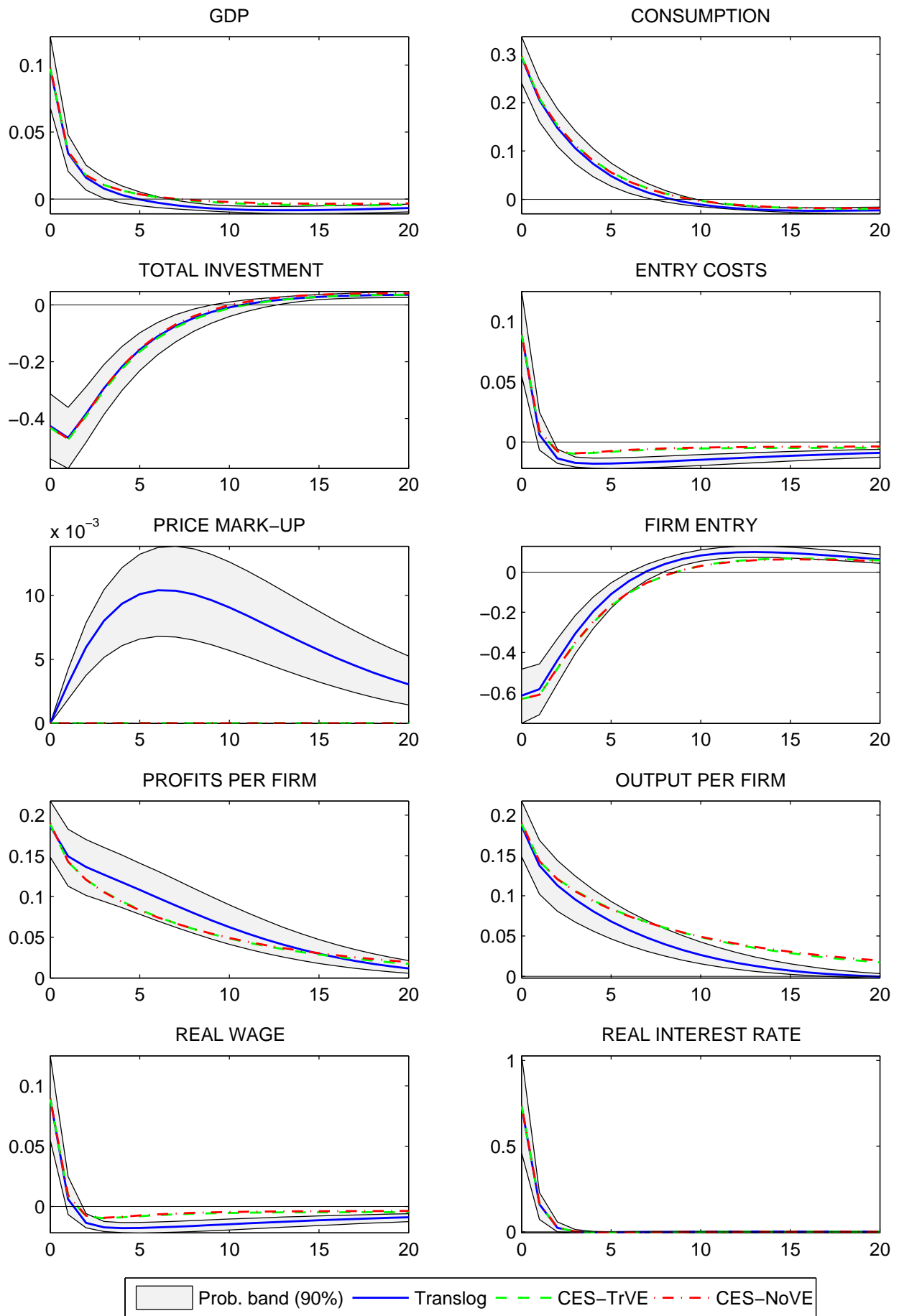


Figure 4: Impulse responses to a preference shock

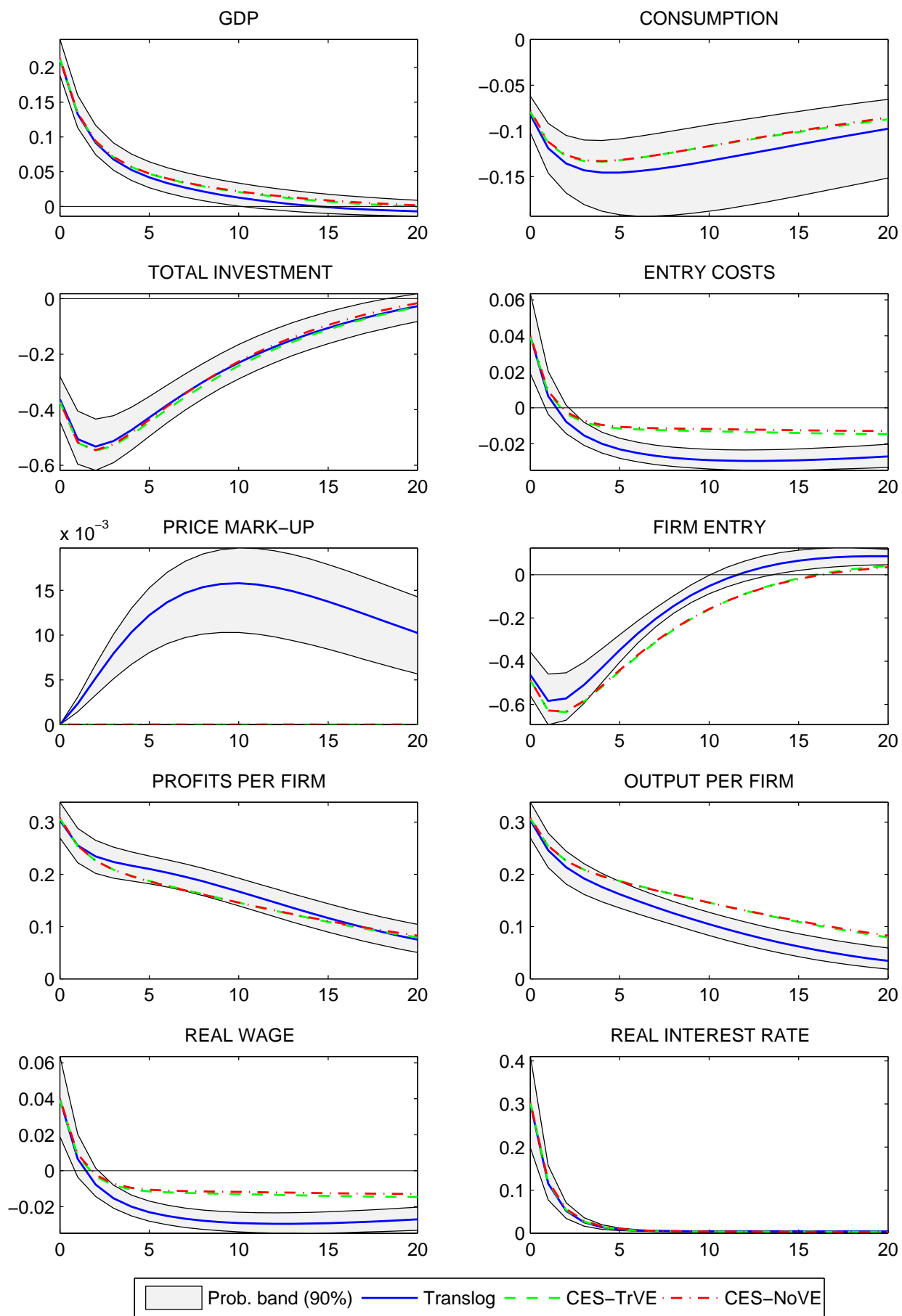


Figure 5: Impulse responses to a government spending shock

is dampened. In the case of entry cost shocks, though, the competition effect changes the GDP response qualitatively.

Overall, the presence of the competition and variety effect substantially amplify (dampen) the impact of labor productivity and wage mark-up (investment-specific technology) shocks on GDP and consumption. In the case of shocks to government spending and preferences, the impact of these mechanisms is only marginal. Inspecting the impulse responses suggests also marginal effects for total investment. In the case of labor productivity and wage mark-up shocks, the responses of total investment are slightly dampened. For the other disturbances, the impacts are negligible. The next section aims to quantify the amplification mechanism by comparing simulated volatilities across the three model frameworks.

6 Quantifying the internal amplification mechanisms

In this section, we quantify the amplification mechanism embedded in the entry model and assess the contribution of the competition and the variety effect. 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. Recall from the previous section that shocks to entry costs generate qualitative different responses across the models. We therefore exclude this shock from our amplification analysis. Including this shock would only slightly change the overall amplification results.

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, 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.²³ Based on the simulated volatility measures, we compute, in the second step, three amplification metrics. The total amplification through both the competition and variety effect is measured as the volatility difference, in percentage terms, between the translog model and the CES-NoVE model. The contribution of the competition effect (CE) is measured by the volatility difference, in percentage terms, between the translog model and the CES-TrVE model. Analogously, the contribution of the variety effect (VE) is computed as the volatility difference, in percentage

²³This 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.

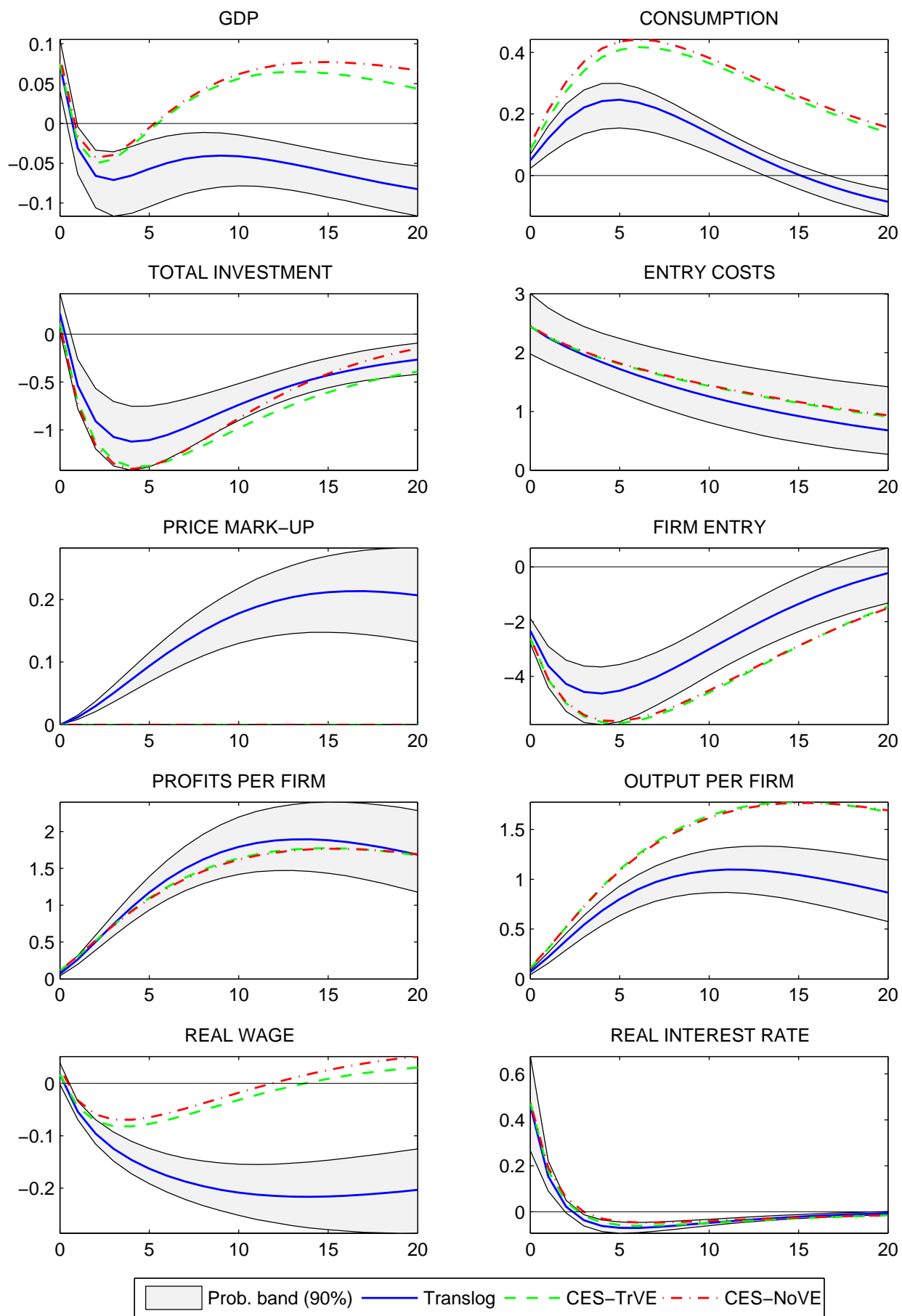


Figure 6: Impulse responses to an entry cost shock

terms, between the CES-TrVE model and the CES-NoVE model. Note that the contributions of the competition and of the variety effect 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 fifth and ninety fifth 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 one to three. 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.²⁴ The overall volatility is measured by the absolute standard deviations of GDP when all five considered structural shocks are active. Columns four to six 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 percent with a 90 percent probability band ranging from 6.1 to 10.1 percent. The competition effect accounts for most amplification across all shocks. Overall, the competition effect increases the volatility of GDP by 6.8 percent with a probability band ranging from 4.5 to 8.4 percent. The increase through the variety effect, on the other hand, only amounts to 1.6 percent with a probability band ranging from 1.0 to 2.0 percent.

Turning to the shock-specific amplification ratios, we obtain the following results. Productivity shocks are amplified by 9.1 percent, wage mark-up shocks by 9.0 percent, and shocks to preferences by 1.8 percent. Contrarily, shocks to investment-specific technology are dampened by 6.5 percent, government spending shocks by 2.5 percent. For all shocks, except for shocks to preferences, the competition and the variety effect work in the same direction. Since the price mark-up μ_t^p decreases with the number of firms and the relative price ρ_t increases with the number of firms, the following rule applies: If GDP and the number of firms are sufficiently positively correlated, both effects amplify GDP. If, on the other hand, the correlation is negative, both effects dampen GDP.²⁵ The

²⁴As in the previous section, GDP is deflated by the relative price ρ_t .

²⁵Note that the variety effect 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 which stems from deflating.

Table 7: Standard deviations, relative volatilities and amplification indicators

	Volatility			Amplification			<i>Corr</i>
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	(<i>X</i> , <i>N</i>)
<i>Std of GDP relative to ... shock</i>							$X = Y^r$
labor prod.	1.0006 [0.9550, 1.0309]	0.9332 [0.8956, 0.9616]	0.9171 [0.8815, 0.9452]	9.1% [6.5%, 10.8%]	7.2% [4.8%, 9.0%]	1.8% [1.1%, 2.1%]	0.92
wage mark-up	0.1811 [0.1287, 0.2620]	0.1690 [0.1201, 0.2456]	0.1661 [0.1180, 0.2418]	9.0% [6.3%, 10.8%]	7.2% [4.7%, 9.0%]	1.8% [1.1%, 2.1%]	0.93
inv. spec. tech.	0.2166 [0.1341, 0.3413]	0.2281 [0.1420, 0.3547]	0.2317 [0.1438, 0.3605]	-6.5% [-7.9%, -4.2%]	-5.0% [-6.5%, -2.9%]	-1.6% [-1.8%, -1.0%]	-0.55
preference	0.0749 [0.0582, 0.0923]	0.0735 [0.0568, 0.0911]	0.0736 [0.0568, 0.0914]	1.8% [0.0%, 3.9%]	2.0% [0.6%, 3.5%]	-0.2% [-0.8%, 0.5%]	0.14
gov. spending	0.0627 [0.0516, 0.0757]	0.0639 [0.0530, 0.0769]	0.0643 [0.0533, 0.0772]	-2.5% [-5.1%, -0.2%]	-2.0% [-4.3%, -0.1%]	-0.6% [-1.0%, 0.0%]	-0.16
<i>Absolute std of GDP</i>							
All five shocks	0.0521 [0.0438, 0.0682]	0.0488 [0.0410, 0.0644]	0.0480 [0.0404, 0.0635]	8.5% [6.1%, 10.1%]	6.8% [4.5%, 8.4%]	1.6% [1.0%, 2.0%]	0.56
<i>Std of consumption relative to ... shock</i>							$X = C^r$
labor prod.	1.0705 [0.9284, 1.2317]	0.9287 [0.8041, 1.0797]	0.8846 [0.7667, 1.0288]	21.0% [14.0%, 26.4%]	15.3% [10.1%, 19.4%]	5.0% [3.5%, 6.1%]	0.97
wage mark-up	0.1995 [0.1416, 0.2909]	0.1741 [0.1221, 0.2584]	0.1659 [0.1160, 0.2478]	20.2% [12.7%, 27.1%]	14.6% [9.0%, 20.0%]	4.9% [3.4%, 6.1%]	0.97
inv. spec. tech.	0.2797 [0.1680, 0.4293]	0.2954 [0.1801, 0.4471]	0.3034 [0.1852, 0.4583]	-7.8% [-10.8%, -5.2%]	-5.3% [-7.9%, -3.1%]	-2.7% [-3.4%, -1.9%]	-0.49
preference	0.2915 [0.2626, 0.3215]	0.2962 [0.2670, 0.3266]	0.2948 [0.2651, 0.3255]	-1.1% [-1.8%, -0.5%]	-1.6% [-2.2%, -1.0%]	0.5% [0.3%, 0.7%]	-0.15
gov. spending	0.1461 [0.1213, 0.1741]	0.1327 [0.1090, 0.1615]	0.1297 [0.1063, 0.1584]	12.7% [7.2%, 17.6%]	10.1% [5.7%, 14.2%]	2.3% [1.4%, 3.1%]	0.95
<i>Absolute std of consumption</i>							
All five shocks	0.0577 [0.0466, 0.0802]	0.0507 [0.0406, 0.0721]	0.0486 [0.0389, 0.0693]	18.7% [12.3%, 23.3%]	13.7% [8.8%, 17.3%]	4.4% [3.2%, 5.4%]	0.55
<i>Std of total investment relative to ... shock</i>							$X = TI^r$
labor prod.	2.2082 [1.7058, 2.5469]	2.3363 [1.8696, 2.6440]	2.2656 [1.8251, 2.5616]	-2.5% [-7.5%, 1.0%]	-5.5% [-9.5%, -2.5%]	3.1% [2.0%, 3.9%]	0.67
wage mark-up	0.3743 [0.2556, 0.5564]	0.3982 [0.2728, 0.5918]	0.3865 [0.2650, 0.5731]	-3.1% [-6.7%, -0.3%]	-6.0% [-8.8%, -3.6%]	3.0% [2.1%, 3.8%]	0.68
inv. spec. tech.	1.2574 [0.7753, 2.0362]	1.2366 [0.7620, 2.0099]	1.2448 [0.7654, 2.0247]	1.0% [-0.1%, 2.2%]	1.7% [0.7%, 2.7%]	-0.7% [-1.0%, -0.3%]	-0.12
preference	0.5985 [0.5303, 0.6943]	0.6094 [0.5389, 0.7079]	0.6004 [0.5297, 0.6987]	-0.3% [-1.5%, 1.1%]	-1.8% [-2.7%, -0.6%]	1.5% [1.1%, 1.9%]	0.34
gov. spending	0.3138 [0.2423, 0.3679]	0.3231 [0.2518, 0.3759]	0.3155 [0.2463, 0.3676]	-0.5% [-3.1%, 1.7%]	-2.9% [-5.0%, -0.9%]	2.4% [1.8%, 2.9%]	0.52
<i>Absolute std of total investment</i>							
All five shocks	0.1203 [0.1079, 0.1375]	0.1261 [0.1134, 0.1436]	0.1231 [0.1109, 0.1401]	-2.3% [-5.3%, 0.0%]	-4.6% [-7.0%, -2.7%]	2.5% [1.7%, 3.1%]	0.44

Note: Volatilities and amplification measures are computed by simulating the model at the posterior mean reported in Table 4. Figures in brackets give the corresponding fifth and ninety fifth 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.

shock-specific amplification is mainly driven by the competition effect, as for total amplification. Except for shocks to preferences, we find that all amplification measures are significantly different from zero at the 5 percent level.

Next, we investigate the components of GDP. The results for consumption and investment are shown in the middle and lower panel 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 percent 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 percent and 20.2 percent, 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 zero at the 5 percent level.

For total investment, the competition effect 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 competition effect and outweighs the positive variety effect. Over all shocks, the volatility in total investment is dampened by -2.3 percent. However, we do not find this result to be significantly different from zero at the 5 percent 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 Appendix C.

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 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. 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 percent. 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 a stronger competition and variety effect in this sample period. The estimate of μ^p implies a point estimate for the competition effect ξ equal to 0.3 with a confidence band ranging from 0.24 to 0.35. The implied variety effect ω is estimated at 0.22 with a confidence band from 0.16 to 0.28. Due to the larger estimates for the competition and variety effect, the amplification measures are also substantially higher when compared to the baseline estimation. The overall amplification of GDP, consumption, and total investment through the competition and the variety effect is now given by 10.3, 24.4, and -4.5 percent, respectively. These numbers are also significantly different from zero at the 5 percent level.

Estimation using mark-up and profit data. Our analysis so far has shown that the competition effect, 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. To see this, note that the model's definition of the price mark-up 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. Both Y_t^c and L_t^c are not observable and are different from the gross domestic product Y_t and overall labor L_t .²⁶ Nevertheless, it is important to check whether our results are robust to the inclusion of a mark-up proxy. As a proxy, we use the growth rate of the inverse labor share $Y_t / (w_t L_t)$. We construct the labor share using data on GDP, hours worked and hourly compensation in the non-farm business sector. To account for the differences between

²⁶An alternative proxy for price mark-ups can be constructed from data on profits using the relation $N_t d_t = (1 - 1/\mu_t^p) Y_t^c$. However, this relation also contains the unobservable variable Y_t^c . Moreover, it requires to use profit data which, as we argue below, suffers from a measurement problem as well.

the proxy and the model-consistent definition of the mark-up, we include the error term $\varepsilon_t^{\mu,me}$ in the measurement equation, where $\varepsilon_t^{\mu,me}$ is assumed to be *i.i.d.* $N(0, \sigma_{\varepsilon^{d,me}}^2)$. This also ensures that the model is not subject to stochastic singularity. The measurement equation then reads as²⁷

$$dl(\text{MARKUP}_t) = 100\Delta\hat{\mu}_t^p + \varepsilon_t^{\mu,me} \quad (25)$$

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.²⁸ We map this measure to overall profits which 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, while 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.* $N(0, \sigma_{\varepsilon^{d,me}}^2)$. The measurement equation for profits then reads as

$$dl(\text{PROFITS}_t) = 100(\Delta\hat{d}_t^r + \Delta\hat{N}_t) + \varepsilon_t^{d,me} \quad (26)$$

Re-estimating the baseline model with data on mark-ups and profits, respectively, we do not find any significant differences in the parameters estimates and the amplification measures, compared to the baseline estimation. The estimated models are able to capture the procyclicality of profits and the countercyclicality of mark-ups in the data. However, most of the variations in the mark-up and profit data are captured by the measurement errors.²⁹ 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 previous section, we have used the same estimated parameter set in all three model frameworks in order to isolate the model-specific competition and variety effect that exclusively result from the different model setups. In this last exercise, we

²⁷Recall that the function dl stands for 100 times the demeaned log-differences operator.

²⁸More details on the source of the profit data and the construction of the data series can be found in Table B.1 and B.2 of Appendix B.

²⁹This 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).

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. All estimates lie within the 90 percent 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 percent and 13.2 percent, 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, Ghironi, and Melitz (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 competition and a variety effect. Both effects are estimated to be statistically significant.

To quantify the strength of this amplification mechanism and to disentangle the competition and the variety effect, we also specify two model frameworks, where either the competition 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 competition and variety effect substantially amplify GDP by 8.5 percent.

The impacts of the competition and variety effect are shock-dependent. For labor productivity and wage mark-up shocks the competition and variety effect amplify the impacts on GDP, but dampen the impacts of shocks to aggregate demand and to investment-specific technology. The competition effect accounts for most amplification, whereas the variety effect 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 new business incorporations. However, this approach neglects the effect of product creation at existing firms. Bernard, Redding, and Schott (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.

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A Model appendix

The price index and the price elasticity of demand. This section derives the price index P_t and the price elasticity of demand ε_t for an individual intermediate good in the translog model. The final goods producers demand intermediate goods $y_{i,t}$ at price $p_{i,t}$ and bundle these intermediate goods to final goods Y_t^C . Under perfect competition and zero profits, total revenues equal total costs. The cost function of a final good producer then equals $P_t Y_t^C$, where P_t is the price and the cost of one final good. In the translog model, $\ln P_t$ is given by the following translog function as proposed by Feenstra (2003):

$$\begin{aligned} \ln P_t = & \alpha_0 + \frac{1}{2} \frac{\tilde{N} - N_t}{\tilde{\sigma} N_t \tilde{N}} + \frac{1}{N_t} \int_0^{N_t} \ln p_{i,t} di \\ & + \frac{1}{2} \frac{\tilde{\sigma}}{N_t} \int_0^{N_t} \int_0^{N_t} \ln p_{i,t} \ln p_{j,t} di dj - \frac{\tilde{\sigma}}{2} \int_0^{N_t} (\ln p_{i,t})^2 di \end{aligned} \quad (\text{A.1})$$

In the following α_0 is normalized to zero.

Under symmetric intermediate goods producers, implying $p_{i,t} = p_{j,t} = p_t$, the translog function (A.1) simplifies to

$$\ln P_t = \frac{1}{2} \frac{\tilde{N} - N_t}{\tilde{\sigma} N_t \tilde{N}} + \ln p_t \quad (\text{A.2})$$

and the relative price reads as

$$\rho_t = \frac{p_t}{P_t} = \exp \left(-\frac{1}{2} \frac{\tilde{N} - N_t}{\tilde{\sigma} N_t \tilde{N}} \right) \quad (\text{A.3})$$

For the derivation of the price elasticity of demand for an individual good, we use the cost share $s_{i,t}$ of the i th production factor, which is defined as

$$s_{i,t} = \frac{p_{i,t} y_{i,t}}{P_t Y_t^C} \quad (\text{A.4})$$

Taking logs of (A.4) and differentiating with respect to $\ln p_{i,t}$ gives

$$\frac{\partial \ln s_{i,t}}{\partial \ln p_{i,t}} = 1 + \frac{\partial \ln y_{i,t}}{\partial \ln p_{i,t}} \quad (\text{A.5})$$

such that we can write the price elasticity as

$$\varepsilon_{i,t} = -\frac{\partial y_{i,t} p_{i,t}}{\partial p_{i,t} y_{i,t}} = -\frac{\partial \ln y_{i,t}}{\partial \ln p_{i,t}} = 1 - \frac{\partial \ln s_{i,t}}{\partial \ln p_{i,t}} = 1 - \frac{\partial s_{i,t}}{\partial \ln p_{i,t}} \frac{1}{s_{i,t}} \quad (\text{A.6})$$

According to Shepard's lemma, the demand for the i th production factor is given by

$$y_{i,t} = \frac{\partial P_t Y_t^C}{\partial p_{i,t}} = Y_t^C \frac{P_t}{p_{i,t}} \frac{\partial \ln P_t}{\partial \ln p_{i,t}} \quad (\text{A.7})$$

Replacing $y_{i,t}$ in (A.4) and differentiating (A.1) with respect to $\ln p_{i,t}$, the cost share can be written as

$$s_{i,t} = \frac{\partial \ln P_t}{\partial \ln p_{i,t}} = \frac{1}{N_t} + \frac{1}{2} \frac{\tilde{\sigma}}{N_t} \int_0^{N_t} \ln p_{i,t} di + \frac{1}{2} \frac{\tilde{\sigma}}{N_t} \int_0^{N_t} \ln p_{i,t} di - \frac{1}{2} \tilde{\sigma} \ln p_{i,t} \quad (\text{A.8})$$

$$= \frac{1}{N_t} + \frac{\tilde{\sigma}}{N_t} \int_0^{N_t} \ln p_{i,t} di - \tilde{\sigma} \ln p_{i,t} \quad (\text{A.9})$$

Differentiating (A.9) with respect to $\ln p_{i,t}$ gives

$$\frac{\partial s_{i,t}}{\partial \ln p_{i,t}} = \frac{\tilde{\sigma}}{N_t} - \tilde{\sigma} \quad (\text{A.10})$$

such that

$$\varepsilon_{i,t} = 1 - \left(\frac{\tilde{\sigma}}{N_t} - \tilde{\sigma} \right) \frac{1}{s_{i,t}} \quad (\text{A.11})$$

which reduces for large N_t to

$$\varepsilon_{i,t} = 1 + \tilde{\sigma} \frac{1}{s_{i,t}} \quad (\text{A.12})$$

Under symmetric prices, the cost share in (A.9) reduces to

$$s_t = \frac{1}{N_t} \quad (\text{A.13})$$

and the price elasticity is given by

$$\varepsilon_t = 1 + \tilde{\sigma} N_t \quad (\text{A.14})$$

The final goods production sector under a CES production technology. This section presents the equations for the final goods production sector under a constant elasticity of substitution (CES) production function as in Benassy (1996). In this case, intermediate goods are combined using the production function $Y_t^C = N_t^{\zeta - \frac{1}{\varepsilon - 1}} \left(\int_0^{N_t} y_{i,t}^{\frac{\varepsilon - 1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon - 1}}$, where $\varepsilon > 1$ is the (constant) elasticity of substitution between the intermediate inputs, and the parameter $\zeta \geq 0$ captures the degree of increasing returns to specialization. The first-order condition for profit maximization yields the demand function for variety i , which is given by $y_{i,t} = \rho_{i,t}^{-\varepsilon} N_t^{\zeta(\varepsilon - 1) - 1} Y_t^C$, where $P_t = N_t^{\frac{1}{\varepsilon - 1} - \zeta} \left(\int_0^{N_t} p_{i,t}^{1 - \varepsilon} di \right)^{\frac{1}{1 - \varepsilon}}$. In a symmetric equilibrium, the price index can be written as $P_t = N_t^{-\zeta} p_t$, implying $\rho_t = N_t^\zeta$. Thus, the degree of returns to specialization ω is equal to ζ . The two different CES-Benassy model variant differ in how we parameterize the variety effect ζ . In the CES-TrVE model, the variety effect is set equal to the value under the translog specification, i.e. $\omega = \zeta = \frac{1}{2}(\mu^p - 1)$. In the CES-NoVE model, $\omega = \zeta = 0$.

The log-linear model. This section presents the log-linearized model equations. A variable without time index denotes its steady-state value. A hat above a variable denotes the percentage deviation from its steady state.

- Consumption Euler equation:

$$\hat{\lambda}_t^C = \text{E}_t \hat{\lambda}_{t+1}^C + \hat{R}_t \quad (\text{A.15})$$

- Shares Euler equation:

$$\hat{v}_t = \text{E}_t \left\{ \hat{\lambda}_{t+t}^C - \hat{\lambda}_t^C + \beta(1 - \delta)\hat{v}_{t+1} + (1 - \beta(1 - \delta))\hat{d}_{t+1} \right\} \quad (\text{A.16})$$

- Capital Euler equation:

$$\hat{Q}_t = \text{E}_t \left\{ \hat{\lambda}_{t+t}^C - \hat{\lambda}_t^C + \beta(1 - \delta^K)\hat{Q}_{t+1} + (1 - \beta(1 - \delta^K))\hat{r}_{t+1}^K \right\} \quad (\text{A.17})$$

- Lagrange multiplier associated with the household's budget constraint:

$$\begin{aligned} \hat{\lambda}_t^C = & \lambda_1 \left(\hat{V}_t + \hat{\chi}_t - b\beta \text{E}_t \{ \hat{V}_{t+1} + \hat{\chi}_{t+1} \} \right) - \lambda_2 \left(\hat{\lambda}_t^S + \hat{S}_t - b\beta \text{E}_t \{ \hat{S}_{t+1} + \hat{\lambda}_{t+1}^S \} \right) \\ & + \lambda_3 \left(\hat{C}_t - b\hat{C}_{t-1} - b\beta \text{E}_t \{ \hat{C}_{t+1} - b\hat{C}_t \} \right), \end{aligned} \quad (\text{A.18})$$

where

$$\begin{aligned}\lambda_1 &= \frac{C(1-b)(1-\beta(1-\gamma))}{(1-b\beta)[(1-\beta(1-\gamma))C(1-b) - \gamma\psi SL^\eta]} \\ \lambda_2 &= \frac{\gamma\psi SL^\eta}{(1-b\beta)[(1-\beta(1-\gamma))C(1-b) - \gamma\psi SL^\eta]} \\ \lambda_3 &= \frac{\gamma\psi SL^\eta}{(1-b)(1-b\beta)[(1-\beta(1-\gamma))C(1-b) - \gamma\psi SL^\eta]}\end{aligned}$$

and the auxiliary variable

$$\hat{V}_t = -\frac{C}{C(1-b) - \psi L^\eta S} (\hat{C}_t - b\hat{C}_{t-1}) + \frac{\psi L^\eta S}{C(1-b) - \psi L^\eta S} (\eta\hat{L}_t + \hat{S}_t) \quad (\text{A.19})$$

- Dynamics of S_t

$$\hat{S}_t = (1-\gamma)\hat{S}_{t-1} + \frac{\gamma}{1-b}\hat{C}_t - \frac{\gamma b}{1-b}\hat{C}_{t-1} \quad (\text{A.20})$$

- Lagrange multiplier associated with S_t :

$$\hat{\lambda}_t^S = \beta(1-\gamma) \text{E}_t \left\{ \hat{\lambda}_{t+1}^S + \hat{S}_{t+1} - \hat{S}_t \right\} + (1-\beta(1-\gamma)) (\eta\hat{L}_t + \hat{V}_t + \hat{\chi}_t) \quad (\text{A.21})$$

- Labor supply:

$$\hat{w}_t = \hat{\mu}_t^w + \hat{V}_t + \theta\hat{L}_t + \hat{S}_t - \hat{\lambda}_t^C + \hat{\chi}_t \quad (\text{A.22})$$

- Optimal pricing equation:

$$\hat{\rho}_t = \hat{\mu}_t^p + \hat{m}c_t \quad (\text{A.23})$$

- Price mark-up:

$$\hat{\mu}_t^p = -\xi\hat{N}_t, \quad (\text{A.24})$$

where $\xi = 1 - \frac{1}{\mu_p}$ in the translog model and $\xi = 0$ in the CES models.

- Relative price:

$$\hat{\rho}_t = \omega \hat{N}_t, \quad (\text{A.25})$$

where $\omega = \frac{1}{2}(\mu^p - 1)$ in the translog model, $\omega = \frac{1}{2}(\mu^p - 1)$ in the CES-TrVE model and $\omega = 0$ in the CES-NoVE model.

- Factor demand equation:

$$\hat{w}_t = \hat{Y}_t^C - \hat{L}_t^C - \hat{\mu}_t^p \quad (\text{A.26})$$

$$\hat{r}_t^K = \hat{Y}_t^C - (\hat{K}_{t-1} + \hat{u}_t) - \hat{\mu}_t^p \quad (\text{A.27})$$

- Total profit income:

$$\hat{D}_t \equiv \hat{N}_t + \hat{d}_t = \frac{1}{\mu^p - 1} \hat{\mu}_t^p + \hat{Y}_t^C \quad (\text{A.28})$$

- Firm entry:

$$\hat{N}_{E,t} = \frac{\beta}{1 + \beta} \text{E}_t \hat{N}_{E,t+1} + \frac{1}{1 + \beta} \hat{N}_{E,t-1} + \frac{1}{(1 + \beta)\kappa_E} (\hat{v}_t - (\hat{w}_t - \hat{z}_t + \hat{f}_{E,t})) \quad (\text{A.29})$$

- Investment in new firms:

$$\hat{I}_{E,t} = \hat{w}_t - \hat{z}_t + \hat{f}_{E,t} + \hat{N}_{E,t} \quad (\text{A.30})$$

- Firm dynamics:

$$\hat{N}_t = (1 - \delta)\hat{N}_{t-1} + \delta\hat{N}_{E,t-1} \quad (\text{A.31})$$

- Investment in physical capital:

$$\hat{I}_t = \frac{\beta}{1 + \beta} \text{E}_t \hat{I}_{t+1} + \frac{1}{1 + \beta} \hat{I}_{t-1} + \frac{1}{\kappa(1 + \beta)} \hat{Q}_t + \hat{u}_t^I \quad (\text{A.32})$$

- Capital accumulation equation:

$$\hat{K}_t = (1 - \delta^K)\hat{K}_{t-1} + \delta^K \hat{I}_t - r^K \hat{u}_t + \delta^K \kappa(1 + \beta)\hat{u}_t^I \quad (\text{A.33})$$

- Capital utilization:

$$\hat{u}_t = \frac{\delta_1}{\delta_2}(\hat{r}_t^K - \hat{Q}_t) \quad (\text{A.34})$$

- Total investment:

$$\hat{T}I_t = \frac{I}{TI}\hat{I}_t + \frac{vN_E}{TI}\hat{I}_{E,t} \quad (\text{A.35})$$

- Labor in entry:

$$\hat{L}_t^E = \hat{f}_{E,t} + \hat{N}_{E,t} - \hat{z}_t \quad (\text{A.36})$$

- Aggregate production function:

$$\hat{Y}_t^C = \hat{\rho}_t + \alpha(\hat{z}_t + \hat{L}_t^C) + (1 - \alpha)(\hat{u}_t + \hat{K}_{t-1}) \quad (\text{A.37})$$

- Gross domestic product:

$$\hat{Y}_t = \frac{Y^C}{Y}\hat{Y}_t^C + \frac{vN_E}{Y}(\hat{w}_t - \hat{z}_t + \hat{f}_{E,t} + \hat{N}_{E,t}) \quad (\text{A.38})$$

- Goods market clearing:

$$\hat{Y}_t^C = \frac{C}{Y^C}\hat{C}_t + \frac{I}{Y^C}\hat{I}_t + \frac{G}{Y^C}\hat{G}_t \quad (\text{A.39})$$

- Resource constraint:

$$\hat{Y}_t = \frac{wL}{Y}(\hat{w}_t + \hat{L}_t) + \frac{Nd}{Y}(\hat{N}_t + \hat{d}_t) + \frac{r^K K}{Y}(\hat{r}_t^K + \hat{K}_{t-1} + \hat{u}_t) \quad (\text{A.40})$$

Shock processes

- Labor productivity:

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_t^z \quad (\text{A.41})$$

- Entry costs:

$$\hat{f}_{E,t} = \rho_{f_E} \hat{f}_{E,t-1} + \varepsilon_t^{f_E} \quad (\text{A.42})$$

- Investment-specific technology:

$$\hat{u}_t^I = \rho_I \hat{u}_{t-1}^I + \varepsilon_t^I \quad (\text{A.43})$$

- Wage mark-up:

$$\hat{\mu}_t^w = \rho_\mu \hat{\mu}_{t-1}^w + \varepsilon_t^\mu + \nu \varepsilon_{t-1}^\mu \quad (\text{A.44})$$

- Government spending:

$$\hat{G}_t = \rho_G \hat{G}_{t-1} + \varepsilon_t^G \quad (\text{A.45})$$

B Data appendix

Table B.1: Data source

Series ID	Description	Source
GDPC96	Real 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 CCAAdj	BEA

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 sensitivity analysis.

Table B.2: Construction of data series

Time Series	Construction	Description
$dl(GDP_t)$	$= dl \left(\frac{GDPC96_t}{CNP160V_t} \right)$	growth rate of real per capita GDP
$dl(CONS_t)$	$= dl \left(\frac{PCND_t + PCESV_t}{CNP160V_t \times GDPDEF_t} \right)$	growth rate of real per capita consumption
$dl(INV_t)$	$= dl \left(\frac{FPI_t + PCDG_t + CBI_t}{CNP160V_t \times GDPDEF_t} \right)$	growth rate of real per capita investment
$dl(WAGE1_t)$	$= dl \left(\frac{PRS85006103_t}{GDPDEF_t} \right)$	growth rate of first measure of real wage
$dl(WAGE2_t)$	$= dl \left(\frac{CES0500000008_t}{GDPDEF_t} \right)$	growth rate of second measure real wage
$l(HOURS_t)$	$= l \left(\frac{PRS85006033_t}{CNP160V_t} \right)$	logarithm of per capita hours worked
$dl(ENTRY_t)$	$= dl \left(\frac{NBI_t}{CNP160V_t} \right)$	growth rate of per capita new firms
$dl(PROFITS_t)$	$= dl \left(\frac{CPATAX_t}{CNP160V_t \times GDPDEF_t} \right)$	growth rate of real per capita profits
$dl(MARKUP_t)$	$= dl \left(\frac{GDPC96_t \times GDPDEF_t}{PRS85006103_t \times PRS85006033_t} \right)$	growth rate of markup measure (inverse labor share)

Note: 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 sensitivity analysis.

C Robustness checks

Table C.1: Results from the Bayesian estimation of the Translog model: Robustness checks

Parameters	Prior distribution				Posterior distribution							
	Type	Mean	STD	Baseline Full sample		Baseline Sub sample		Baseline + Profit data Full sample		Baseline + Markup data Full sample		
				Mean	[5% , 95%]	Mean	[5% , 95%]	Mean	[5% , 95%]	Mean	[5% , 95%]	
<i>Structural parameters</i>												
Labor share in production	α	Beta	0.7	0.2	0.85	[0.81 , 0.90]	0.91	[0.86 , 0.96]	0.85	[0.81 , 0.90]	0.86	[0.81 , 0.90]
Labor utility	θ	Gamma	2.0	1.0	3.64	[1.92 , 5.80]	4.14	[2.18 , 6.57]	3.62	[1.90 , 5.77]	3.60	[1.90 , 5.77]
Wealth elast. labor supply	γ	Beta	0.5	0.2	0.79	[0.63 , 0.93]	0.78	[0.59 , 0.93]	0.80	[0.63 , 0.93]	0.79	[0.63 , 0.93]
Consumption habit	b	Beta	0.5	0.2	0.76	[0.71 , 0.80]	0.77	[0.71 , 0.82]	0.75	[0.70 , 0.80]	0.75	[0.70 , 0.80]
Investment adj. cost	κ_I	Gamma	4.0	1.0	3.82	[2.59 , 5.28]	3.81	[2.47 , 5.38]	3.83	[2.60 , 5.30]	3.93	[2.68 , 5.40]
Inv. elast. of capital util.	$\frac{\partial z}{\partial 1}$	Igamma	1.0	1.0	0.55	[0.33 , 0.89]	0.53	[0.32 , 0.84]	0.55	[0.33 , 0.90]	0.53	[0.33 , 0.85]
Price mark-up	μ^P	Gamma	1.3	0.2	1.26	[1.16 , 1.36]	1.43	[1.31 , 1.55]	1.26	[1.16 , 1.36]	1.26	[1.17 , 1.36]
Entry adj. cost	κ_E	Gamma	4.0	1.0	1.50	[1.09 , 1.99]	1.46	[1.01 , 2.00]	1.49	[1.08 , 1.98]	1.49	[1.07 , 1.97]
<i>Autocorrelation of shock processes</i>												
Labor productivity	ρ_z	Beta	0.5	0.2	0.96	[0.94 , 0.98]	0.98	[0.97 , 0.99]	0.96	[0.94 , 0.98]	0.96	[0.94 , 0.98]
Wage mark-up	ρ_μ	Beta	0.5	0.2	0.97	[0.95 , 0.98]	0.95	[0.93 , 0.97]	0.97	[0.95 , 0.98]	0.97	[0.95 , 0.98]
Invest. spec. tech.	ρ_I	Beta	0.5	0.2	0.24	[0.12 , 0.38]	0.19	[0.07 , 0.33]	0.25	[0.12 , 0.38]	0.24	[0.12 , 0.38]
Gov. spending	ρ_G	Beta	0.5	0.2	0.92	[0.88 , 0.94]	0.91	[0.87 , 0.95]	0.91	[0.88 , 0.94]	0.92	[0.88 , 0.95]
Entry cost	ρ_{f_E}	Beta	0.5	0.2	0.95	[0.91 , 0.98]	0.98	[0.96 , 0.99]	0.95	[0.91 , 0.98]	0.95	[0.91 , 0.98]
<i>Standard deviation of innovations</i>												
Labor prod.	σ_{ε^z}	Igamma	2.0	1	0.80	[0.70 , 0.90]	0.74	[0.65 , 0.85]	0.79	[0.70 , 0.90]	0.80	[0.70 , 0.90]
Wage mark-up	σ_{ε^μ}	Igamma	2.0	1	4.30	[3.00 , 5.95]	4.98	[3.36 , 6.98]	4.28	[2.99 , 5.92]	4.28	[2.98 , 5.93]
Invest. spec. tech.	σ_{ε^I}	Igamma	2.0	1	3.99	[2.39 , 6.54]	12.00	[4.91 , 26.14]	4.02	[2.39 , 6.69]	4.01	[2.42 , 6.50]
Preference	$\sigma_{\varepsilon^\chi}$	Igamma	2.0	1	1.46	[1.07 , 1.91]	1.64	[1.17 , 2.20]	1.45	[1.07 , 1.90]	1.45	[1.07 , 1.88]
Gov. spending	σ_{ε^G}	Igamma	2.0	1	1.87	[1.71 , 2.03]	1.78	[1.61 , 1.96]	1.87	[1.72 , 2.03]	1.87	[1.72 , 2.03]
Entry cost	$\sigma_{\varepsilon^{f_E}}$	Igamma	2.0	1	2.43	[1.96 , 2.97]	2.58	[2.12 , 3.08]	2.44	[1.97 , 2.99]	2.42	[1.95 , 2.97]
<i>Moving average parameter and loading coefficient</i>												
Wage mark-up shock	ν	Normal	0.0	0.2	0.41	[0.26 , 0.56]	0.27	[0.08 , 0.45]	0.41	[0.26 , 0.56]	0.41	[0.26 , 0.56]
Loading coefficient	λ	Normal	1.0	2.0	0.13	[0.06 , 0.19]	0.13	[0.04 , 0.22]	0.13	[0.06 , 0.19]	0.13	[0.06 , 0.19]

Note: Using a Random Walk Metropolis Hastings algorithm, we generate 2 chains of 2 Mio. 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. In our baseline estimation, the data sample ranges from 1964:Q1 to 2012:Q2 (full data sample) and the data set consists of data series on GDP, consumption, investment, hours worked, firm entry, and two wage measures. In the sub sample estimation, the data sample only ranges until 1998:Q3.

Table C.2: Standard deviations, relative volatilities and amplification indicators using estimated parameters from the subsample estimation

	Volatility			Amplification			<i>Corr</i> (<i>X</i> , <i>N</i>)
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	
<i>Std of GDP relative to ... shock</i>							<i>X = Y^r</i>
labor prod.	1.0382 [1.0066, 1.0556]	0.9402 [0.9065, 0.9580]	0.9304 [0.9058, 0.9483]	11.6% [9.3%, 13.2%]	10.4% [8.6%, 12.7%]	1.1 % [-0.5%, 1.8%]	0.95
wage mark-up	0.1628 [0.1067, 0.2308]	0.1470 [0.0957, 0.2096]	0.1456 [0.0956, 0.2088]	11.9% [9.4%, 13.4%]	10.8% [8.9%, 12.9%]	1.0 % [-0.5%, 1.8%]	0.89
inv. spec. tech.	0.1031 [0.0315, 0.1821]	0.1104 [0.0337, 0.1941]	0.1113 [0.0336, 0.1966]	-7.4% [-8.2%, -5.1%]	-6.7% [-7.6%, -5.1%]	-0.8 % [-1.4%, 0.5%]	-0.59
preference	0.0594 [0.0437, 0.0691]	0.0593 [0.0460, 0.0684]	0.0594 [0.0453, 0.0687]	-0.0% [-5.3%, 2.5%]	0.2% [-7.0%, 2.5%]	-0.2 % [-0.7%, 2.1%]	0.08
gov. spending	0.0648 [0.0533, 0.0781]	0.0678 [0.0572, 0.0812]	0.0681 [0.0574, 0.0812]	-4.8% [-8.2%, -2.7%]	-4.4% [-8.2%, -2.4%]	-0.5 % [-0.8%, 0.3%]	-0.22
<i>Absolute std of GDP</i>							
All five shocks	0.0541 [0.0442, 0.0786]	0.0495 [0.0403, 0.0715]	0.0491 [0.0402, 0.0714]	10.3% [8.7%, 12.1%]	9.3% [8.1%, 11.7%]	0.9 % [-0.5%, 1.6%]	0.52
<i>Std of consumption relative to ... shock</i>							<i>X = C^r</i>
labor prod.	1.3014 [1.1901, 1.4355]	1.0971 [0.9802, 1.2366]	1.0287 [0.9186, 1.1631]	26.5% [21.3%, 32.3%]	18.6% [14.7%, 23.3%]	6.7 % [5.5%, 7.8%]	0.99
wage mark-up	0.1766 [0.1164, 0.2545]	0.1416 [0.0895, 0.2056]	0.1322 [0.0835, 0.1935]	33.5% [26.3%, 42.8%]	24.7% [18.9%, 32.6%]	7.1 % [5.8%, 8.3%]	0.98
inv. spec. tech.	0.1359 [0.0394, 0.2378]	0.1469 [0.0431, 0.2554]	0.1501 [0.0436, 0.2625]	-9.5% [-12.5%, -6.5%]	-7.5% [-10.6%, -5.4%]	-2.2 % [-3.0%, -0.6%]	-0.59
preference	0.2893 [0.2497, 0.3227]	0.2961 [0.2575, 0.3299]	0.2949 [0.2560, 0.3293]	-1.9% [-2.8%, -1.3%]	-2.3% [-3.2%, -1.8%]	0.4 % [0.1%, 0.7%]	-0.14
gov. spending	0.1407 [0.1124, 0.1747]	0.1201 [0.0909, 0.1559]	0.1160 [0.0875, 0.1517]	21.3% [13.7%, 31.0%]	17.1% [10.9%, 25.6%]	3.6 % [2.4%, 4.5%]	0.96
<i>Absolute std of consumption</i>							
All five shocks	0.0651 [0.0517, 0.1043]	0.0553 [0.0428, 0.0897]	0.0524 [0.0405, 0.0846]	24.4% [20.8%, 30.6%]	17.7% [14.6%, 22.6%]	5.6 % [5.0%, 7.0%]	0.60
<i>Std of total investment relative to ... shock</i>							<i>X = TI^r</i>
labor prod.	1.5248 [1.0374, 1.8562]	1.7096 [1.2268, 2.0340]	1.6826 [1.2207, 1.9967]	-9.4% [-16.5%, -5.1%]	-10.8% [-16.5%, -7.5%]	1.6 % [-0.2%, 2.7%]	0.71
wage mark-up	0.3509 [0.2230, 0.4958]	0.3778 [0.2448, 0.5403]	0.3703 [0.2416, 0.5326]	-5.2% [-10.6%, -2.2%]	-7.1% [-11.2%, -4.9%]	2.0 % [0.5%, 3.1%]	0.58
inv. spec. tech.	0.5215 [0.1654, 0.9305]	0.5113 [0.1614, 0.9157]	0.5130 [0.1612, 0.9202]	1.6% [0.6%, 3.2%]	2.0% [1.2%, 3.1%]	-0.3 % [-0.7%, 0.2%]	-0.08
preference	0.5774 [0.4818, 0.6933]	0.5880 [0.4911, 0.7084]	0.5809 [0.4844, 0.7035]	-0.6% [-1.8%, 0.4%]	-1.8% [-2.6%, -1.1%]	1.2 % [0.7%, 1.7%]	0.28
gov. spending	0.2818 [0.1916, 0.3266]	0.2941 [0.2051, 0.3395]	0.2889 [0.2026, 0.3341]	-2.5% [-6.7%, -0.1%]	-4.2% [-7.5%, -2.4%]	1.8 % [0.7%, 2.5%]	0.45
<i>Absolute std of total investment</i>							
All five shocks	0.1140 [0.0950, 0.1240]	0.1208 [0.1026, 0.1330]	0.1193 [0.1018, 0.1314]	-4.5% [-10.1%, -2.6%]	-5.6% [-10.3%, -4.5%]	1.2 % [0.2%, 2.2%]	0.25

Note: Volatilities and amplification measures are computed by simulating the model at the posterior mean reported in Table C.1. Figures in brackets give the corresponding fifth and ninety fifth 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.

Table C.3: Standard deviations, relative volatilities and amplification indicators using estimated parameters from the estimation with mark-up data

	Volatility			Amplification			<i>Corr</i> (<i>X</i> , <i>N</i>)
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	
<i>Std of GDP relative to ... shock</i>							<i>X = Y^r</i>
labor prod.	1.0019 [0.9509, 1.0304]	0.9334 [0.8930, 0.9614]	0.9175 [0.8786, 0.9451]	9.2% [6.7%, 10.9%]	7.3% [5.0%, 9.1%]	1.7 % [1.2%, 2.1%]	0.92
wage mark-up	0.1824 [0.1285, 0.2592]	0.1700 [0.1193, 0.2434]	0.1671 [0.1174, 0.2395]	9.1% [6.6%, 10.9%]	7.3% [4.9%, 9.1%]	1.7 % [1.2%, 2.1%]	0.93
inv. spec. tech.	0.2106 [0.1332, 0.3322]	0.2220 [0.1413, 0.3450]	0.2254 [0.1431, 0.3506]	-6.6% [-8.1%, -4.4%]	-5.1% [-6.7%, -3.1%]	-1.5 % [-1.8%, -1.1%]	-0.55
preference	0.0747 [0.0595, 0.0919]	0.0734 [0.0584, 0.0907]	0.0736 [0.0585, 0.0909]	1.6% [-0.1%, 3.5%]	1.9% [0.6%, 3.3%]	-0.3 % [-0.8%, 0.4%]	0.13
gov. spending	0.0632 [0.0526, 0.0751]	0.0645 [0.0541, 0.0764]	0.0649 [0.0543, 0.0768]	-2.7% [-5.1%, -0.3%]	-2.1% [-4.3%, -0.2%]	-0.6 % [-1.0%, -0.1%]	-0.17
<i>Absolute std of GDP</i>							
All five shocks	0.0519 [0.0437, 0.0679]	0.0486 [0.0408, 0.0641]	0.0478 [0.0402, 0.0630]	8.6% [6.3%, 10.1%]	6.8% [4.7%, 8.4%]	1.6 % [1.1%, 2.0%]	0.56
<i>Std of consumption relative to ... shock</i>							<i>X = C^r</i>
labor prod.	1.0768 [0.9221, 1.2289]	0.9320 [0.8005, 1.0771]	0.8872 [0.7642, 1.0270]	21.4% [14.6%, 26.5%]	15.5% [10.5%, 19.4%]	5.0 % [3.6%, 6.1%]	0.97
wage mark-up	0.2012 [0.1411, 0.2914]	0.1750 [0.1216, 0.2583]	0.1668 [0.1153, 0.2473]	20.6% [13.4%, 26.9%]	14.9% [9.4%, 19.8%]	5.0 % [3.5%, 6.1%]	0.97
inv. spec. tech.	0.2732 [0.1723, 0.4240]	0.2889 [0.1846, 0.4422]	0.2968 [0.1896, 0.4527]	-8.0% [-10.5%, -5.2%]	-5.4% [-7.6%, -3.2%]	-2.7 % [-3.4%, -1.9%]	-0.50
preference	0.2922 [0.2663, 0.3216]	0.2970 [0.2705, 0.3269]	0.2957 [0.2689, 0.3259]	-1.2% [-1.8%, -0.5%]	-1.6% [-2.2%, -1.0%]	0.5 % [0.3%, 0.7%]	-0.15
gov. spending	0.1448 [0.1215, 0.1717]	0.1312 [0.1087, 0.1594]	0.1281 [0.1060, 0.1563]	13.0% [7.7%, 17.6%]	10.4% [6.1%, 14.2%]	2.4 % [1.5%, 3.1%]	0.95
<i>Absolute std of consumption</i>							
All five shocks	0.0576 [0.0467, 0.0799]	0.0505 [0.0406, 0.0716]	0.0484 [0.0390, 0.0688]	18.9% [13.0%, 23.3%]	13.9% [9.3%, 17.2%]	4.4 % [3.3%, 5.4%]	0.55
<i>Std of total investment relative to ... shock</i>							<i>X = TI^r</i>
labor prod.	2.1944 [1.7275, 2.5336]	2.3274 [1.8844, 2.6394]	2.2571 [1.8347, 2.5570]	-2.8% [-7.2%, 0.8%]	-5.7% [-9.4%, -2.7%]	3.1 % [2.2%, 3.9%]	0.66
wage mark-up	0.3768 [0.2592, 0.5395]	0.4017 [0.2768, 0.5752]	0.3899 [0.2693, 0.5575]	-3.3% [-6.5%, -0.5%]	-6.2% [-8.7%, -3.8%]	3.0 % [2.3%, 3.8%]	0.68
inv. spec. tech.	1.2283 [0.7792, 1.9548]	1.2074 [0.7665, 1.9230]	1.2152 [0.7707, 1.9378]	1.1% [-0.0%, 2.2%]	1.7% [0.8%, 2.7%]	-0.7 % [-1.0%, -0.4%]	-0.11
preference	0.6002 [0.5326, 0.6911]	0.6115 [0.5415, 0.7046]	0.6025 [0.5325, 0.6955]	-0.4% [-1.6%, 0.9%]	-1.9% [-2.8%, -0.7%]	1.5 % [1.1%, 1.9%]	0.34
gov. spending	0.3123 [0.2444, 0.3601]	0.3219 [0.2540, 0.3687]	0.3143 [0.2481, 0.3608]	-0.6% [-2.9%, 1.5%]	-3.0% [-4.9%, -1.1%]	2.4 % [1.9%, 3.0%]	0.52
<i>Absolute std of total investment</i>							
All five shocks	0.1201 [0.1074, 0.1359]	0.1261 [0.1128, 0.1425]	0.1231 [0.1103, 0.1389]	-2.4% [-5.1%, -0.1%]	-4.7% [-6.9%, -2.9%]	2.4 % [1.8%, 3.1%]	0.43

Note: Volatilities and amplification measures are computed by simulating the model at the posterior mean reported in Table C.1. Figures in brackets give the corresponding fifth and ninety fifth 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.

Table C.4: Standard deviations, relative volatilities and amplification indicators using estimated parameters from the estimation with profit data

	Volatility			Amplification			<i>Corr</i> (<i>X</i> , <i>N</i>)
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	
<i>Std of GDP relative to ... shock</i>							<i>X = Y^r</i>
labor prod.	1.0056 [0.9570, 1.0335]	0.9341 [0.8962, 0.9618]	0.9183 [0.8823, 0.9454]	9.5% [6.8%, 11.1%]	7.7% [5.2%, 9.6%]	1.7 % [0.7%, 2.1%]	0.92
wage mark-up	0.1763 [0.1235, 0.2540]	0.1639 [0.1144, 0.2386]	0.1611 [0.1126, 0.2347]	9.4% [6.7%, 11.1%]	7.6% [5.0%, 9.7%]	1.7 % [0.6%, 2.1%]	0.93
inv. spec. tech.	0.2002 [0.0922, 0.3267]	0.2115 [0.0985, 0.3405]	0.2148 [0.0990, 0.3462]	-6.8% [-8.0%, -4.4%]	-5.4% [-6.8%, -3.1%]	-1.5 % [-1.8%, -0.5%]	-0.56
preference	0.0721 [0.0536, 0.0898]	0.0707 [0.0534, 0.0886]	0.0708 [0.0535, 0.0888]	1.8% [-1.1%, 4.0%]	2.0% [-0.9%, 3.6%]	-0.2 % [-0.7%, 0.6%]	0.14
gov. spending	0.0625 [0.0529, 0.0751]	0.0639 [0.0543, 0.0764]	0.0643 [0.0546, 0.0768]	-2.7% [-5.5%, -0.2%]	-2.1% [-4.9%, -0.2%]	-0.6 % [-0.9%, 0.0%]	-0.15
<i>Absolute std of GDP</i>							
All five shocks	0.0522 [0.0439, 0.0677]	0.0488 [0.0410, 0.0637]	0.0480 [0.0405, 0.0627]	8.8% [6.4%, 10.3%]	7.1% [4.8%, 9.0%]	1.6 % [0.6%, 2.0%]	0.56
<i>Std of consumption relative to ... shock</i>							<i>X = C^r</i>
labor prod.	1.0918 [0.9330, 1.2668]	0.9411 [0.8091, 1.0997]	0.8943 [0.7717, 1.0451]	22.1% [14.9%, 27.8%]	16.0% [10.7%, 20.5%]	5.2 % [3.7%, 6.3%]	0.97
wage mark-up	0.1954 [0.1347, 0.2881]	0.1692 [0.1153, 0.2539]	0.1609 [0.1091, 0.2435]	21.4% [13.6%, 29.6%]	15.5% [9.6%, 22.2%]	5.2 % [3.6%, 6.3%]	0.98
inv. spec. tech.	0.2589 [0.1227, 0.4158]	0.2744 [0.1322, 0.4347]	0.2820 [0.1351, 0.4453]	-8.2% [-11.1%, -5.5%]	-5.7% [-8.3%, -3.4%]	-2.7 % [-3.5%, -1.9%]	-0.50
preference	0.2901 [0.2613, 0.3195]	0.2950 [0.2666, 0.3245]	0.2935 [0.2650, 0.3233]	-1.2% [-2.1%, -0.5%]	-1.6% [-2.5%, -1.0%]	0.5 % [0.3%, 0.7%]	-0.15
gov. spending	0.1457 [0.1218, 0.1704]	0.1313 [0.1082, 0.1569]	0.1281 [0.1053, 0.1536]	13.7% [8.0%, 19.6%]	10.9% [6.3%, 16.0%]	2.5 % [1.6%, 3.2%]	0.95
<i>Absolute std of consumption</i>							
All five shocks	0.0583 [0.0473, 0.0802]	0.0510 [0.0411, 0.0717]	0.0488 [0.0393, 0.0687]	19.5% [13.1%, 25.2%]	14.3% [9.4%, 18.9%]	4.6 % [3.3%, 5.6%]	0.55
<i>Std of total investment relative to ... shock</i>							<i>X = TI^r</i>
labor prod.	2.1574 [1.5919, 2.5244]	2.2925 [1.7766, 2.6176]	2.2257 [1.7411, 2.5355]	-3.1% [-10.2%, 0.9%]	-5.9% [-11.5%, -2.6%]	3.0 % [1.5%, 3.9%]	0.66
wage mark-up	0.3603 [0.2492, 0.5185]	0.3846 [0.2682, 0.5539]	0.3736 [0.2615, 0.5382]	-3.6% [-8.2%, -0.3%]	-6.3% [-9.8%, -3.7%]	2.9 % [1.6%, 3.8%]	0.67
inv. spec. tech.	1.1486 [0.5220, 1.9399]	1.1295 [0.5081, 1.9112]	1.1368 [0.5092, 1.9255]	1.0% [-0.1%, 2.4%]	1.7% [0.7%, 2.8%]	-0.7 % [-1.0%, -0.3%]	-0.12
preference	0.5978 [0.5321, 0.6903]	0.6084 [0.5405, 0.7032]	0.5995 [0.5315, 0.6949]	-0.3% [-1.5%, 1.0%]	-1.8% [-2.7%, -0.7%]	1.5 % [1.0%, 1.9%]	0.33
gov. spending	0.3141 [0.2426, 0.3660]	0.3237 [0.2535, 0.3737]	0.3162 [0.2483, 0.3657]	-0.7% [-4.0%, 1.6%]	-3.0% [-5.6%, -0.9%]	2.4 % [1.6%, 2.9%]	0.51
<i>Absolute std of total investment</i>							
All five shocks	0.1200 [0.1066, 0.1345]	0.1259 [0.1128, 0.1412]	0.1231 [0.1105, 0.1379]	-2.5% [-6.8%, 0.0%]	-4.8% [-7.9%, -2.8%]	2.3 % [1.2%, 3.1%]	0.43

Note: Volatilities and amplification measures are computed by simulating the model at the posterior mean reported in Table C.1. Figures in brackets give the corresponding fifth and ninety fifth 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.

Table C.5: Results from the Bayesian estimation of the Translog and the CES models

Parameters	Prior distribution				Posterior distribution					
	Type	Mean	STD	Translog		CES-TrVE		CES-NoVE		
				Mean	[5% , 95%]	Mean	[5% , 95%]	Mean	[5% , 95%]	
<i>Structural parameters</i>										
Labor share in production	α	Beta	0.7	0.2	0.85	[0.81 , 0.90]	0.85	[0.83 , 0.88]	0.85	[0.83 , 0.88]
Labor utility	θ	Gamma	2.0	1.0	3.64	[1.92 , 5.80]	3.83	[2.11 , 5.95]	3.91	[2.17 , 6.06]
Wealth elast. labor supply	γ	Beta	0.5	0.2	0.79	[0.63 , 0.93]	0.79	[0.63 , 0.93]	0.79	[0.62 , 0.93]
Consumption habit	b	Beta	0.5	0.2	0.76	[0.71 , 0.80]	0.75	[0.70 , 0.80]	0.74	[0.69 , 0.79]
Investment adj. cost	κ_I	Gamma	4.0	1.0	3.82	[2.59 , 5.28]	3.70	[2.53 , 5.09]	3.61	[2.44 , 4.99]
Inv. elast. of capital util.	$\frac{\delta_2}{\delta_1}$	Igamma	1.0	1.0	0.55	[0.33 , 0.89]	0.55	[0.34 , 0.89]	0.56	[0.34 , 0.90]
Price mark-up	μ^p	Gamma	1.3	0.2	1.26	[1.16 , 1.36]	–	–	–	–
Entry adj. cost	κ_E	Gamma	4.0	1.0	1.50	[1.09 , 1.99]	1.56	[1.13 , 2.06]	1.52	[1.09 , 2.02]
<i>Autocorrelation of shock processes</i>										
Labor productivity	ρ_z	Beta	0.5	0.2	0.96	[0.94 , 0.98]	0.96	[0.94 , 0.98]	0.96	[0.94 , 0.98]
Wage mark-up	ρ_μ	Beta	0.5	0.2	0.97	[0.95 , 0.98]	0.97	[0.95 , 0.98]	0.97	[0.95 , 0.98]
Invest. spec. tech.	ρ_I	Beta	0.5	0.2	0.24	[0.12 , 0.38]	0.23	[0.11 , 0.36]	0.22	[0.10 , 0.35]
Gov. spending	ρ_G	Beta	0.5	0.2	0.92	[0.88 , 0.94]	0.92	[0.88 , 0.95]	0.92	[0.89 , 0.95]
Entry cost	ρ_{fE}	Beta	0.5	0.2	0.95	[0.91 , 0.98]	0.94	[0.89 , 0.98]	0.94	[0.89 , 0.98]
<i>Standard deviation of innovations</i>										
Labor prod.	$\sigma_{\varepsilon z}$	Igamma	2.0	1	0.80	[0.70 , 0.90]	0.79	[0.71 , 0.89]	0.80	[0.72 , 0.89]
Wage mark-up	$\sigma_{\varepsilon \mu}$	Igamma	2.0	1	4.30	[3.00 , 5.95]	4.39	[3.12 , 5.96]	4.43	[3.14 , 6.01]
Invest. spec. tech.	$\sigma_{\varepsilon I}$	Igamma	2.0	1	3.99	[2.39 , 6.54]	3.91	[3.21 , 4.69]	3.94	[3.25 , 4.71]
Preference	$\sigma_{\varepsilon \lambda}$	Igamma	2.0	1	1.46	[1.07 , 1.91]	1.42	[1.06 , 1.85]	1.36	[1.01 , 1.75]
Gov. spending	$\sigma_{\varepsilon G}$	Igamma	2.0	1	1.87	[1.71 , 2.03]	1.87	[1.72 , 2.03]	1.87	[1.72 , 2.04]
Entry cost	$\sigma_{\varepsilon fE}$	Igamma	2.0	1	2.43	[1.96 , 2.97]	2.04	[1.57 , 2.55]	1.98	[1.53 , 2.49]
<i>Moving average parameter and loading coefficient</i>										
Wage mark-up shock	ν	Normal	0.0	0.2	0.41	[0.26 , 0.56]	0.42	[0.27 , 0.56]	0.42	[0.27 , 0.56]
Loading coefficient	λ	Normal	1.0	2.0	0.13	[0.06 , 0.19]	0.13	[0.06 , 0.19]	0.13	[0.06 , 0.19]

Note: Using a Random Walk Metropolis Hastings algorithm, we generate 2 chains of 2 Mio. 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. To estimate the CES models, we calibrate the steady state price mark-up at the posterior mean of the translog estimation. The data set ranges from 1964:Q1 to 2012:Q2 and consists of data series on GDP, consumption, investment, hours worked, firm entry, and two wage measures.

Table C.6: Standard deviations, relative volatilities and amplification indicators using estimated translog and CES models

	Volatility			Amplification			Corr
	Translog	CES-TrVE	CES-NoVE	Total	CE	VE	(X, N)
<i>Std of GDP relative to ... shock</i>							$X = Y^r$
labor prod.	1.0006	0.9365	0.9202	8.7%	6.8%	1.8 %	0.92
wage mark-up	0.1811	0.1628	0.1599	13.2%	11.3%	1.8 %	0.93
inv. spec. tech.	0.2166	0.2078	0.2111	2.6%	4.3%	-1.6 %	-0.55
preference	0.0749	0.0766	0.0768	-2.4%	-2.3%	-0.2 %	0.14
gov. spending	0.0627	0.0608	0.0611	2.6%	3.2%	-0.6 %	-0.16
<i>Std of consumption relative to ... shock</i>							$X = C^r$
labor prod.	1.0705	0.9396	0.8939	19.8%	13.9%	5.1 %	0.97
wage mark-up	0.1995	0.1731	0.1649	21.0%	15.2%	5.0 %	0.97
inv. spec. tech.	0.2797	0.2695	0.2769	1.0%	3.8%	-2.7 %	-0.49
preference	0.2915	0.3023	0.3010	-3.2%	-3.6%	0.4 %	-0.15
gov. spending	0.1461	0.1384	0.1352	8.1%	5.6%	2.4 %	0.95
<i>Std of total investment relative to ... shock</i>							$X = TI^r$
labor prod.	2.2082	2.2929	2.2256	-0.8%	-3.7%	3.0 %	0.67
wage mark-up	0.3743	0.3580	0.3480	7.6%	4.6%	2.9 %	0.68
inv. spec. tech.	1.2574	1.1249	1.1317	11.1%	11.8%	-0.6 %	-0.12
preference	0.5985	0.6090	0.6005	-0.3%	-1.7%	1.4 %	0.34
gov. spending	0.3138	0.3152	0.3080	1.9%	-0.4%	2.3 %	0.52

Note: Volatilities and amplification measures are computed at the respective posterior mean given in Table C.5. Note that we are not able to give the probability bands for our amplification measures in the above specification. This would require to know the joint posterior distribution under the translog and the CES models. The contemporaneous correlation in the last column is based on simulated data from the translog model at the posterior mean.