Firm Entry, Endogenous Wage Moderation, and Labor Market Dynamics*

Andrea Colciago†
De Nederlandsche Bank
and University of Milano Bicocca

Stefano Fasani‡
Lancaster University

Lorenza Rossi§
Lancaster University

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Abstract

Profit-seeking is a key driver of new business creation, which, in turn, significantly influences unemployment dynamics. This paper uses US data to estimate the joint responses of firm entry, profits, unemployment, hours worked, and other aggregates to commonly studied supply shocks. Our analysis finds a positive correlation between firm entry, profits, and total hours worked, alongside a negative correlation with the unemployment rate. We develop and estimate a general equilibrium model that captures these dynamics.

Keywords: Entry, Unemployment, Bayesian Analysis, Search and Matching.
JEL codes: C5, E32

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†Email: andreacolciago@gmail.com

‡Email: s.fasani@lancaster.ac.uk

§Corresponding Author: Department of Economics, Lancaster University Management School (LUMS), Bailrigg, LA14YX, Lancaster UK. Email: l.rossi@lancaster.ac.uk

1 Introduction

The creation of firms and jobs takes place within frictional labor and goods markets. These frictions are reflected in the simultaneous presence of job vacancies and unemployed workers seeking employment, as well as in the existence of economic profits. The quest for profits is a key driver of firm creation, with newly established firms significantly influencing unemployment dynamics in the United States. Using a Bayesian Vector Auto Regressive (BVAR) framework, we identify the effects of technology, price markup, and workers' wage bargaining power shocks on firm entry, profits, unemployment, hours worked, and other relevant aggregates in the U.S. economy. Our findings reveal a distinct pattern in response to these shocks: firm entry is positively correlated with profits and hours worked, while it is negatively correlated with the rate of unemployment. To explain these empirical results, we develop and estimate a macroeconomic model that aligns with the empirical findings, thereby providing a theoretical foundation for understanding the observed relationships.

Our model integrates the search and matching model (SAM, henceforth) into a framework where firm entry (E) is frictional, and final goods markets are monopolistically competitive. We refer to the resulting framework as the Entry Search and Matching Model (ESAM, henceforth). In ESAM, firms enter the market until the expected discounted value of future profits equals a sunk entry cost, as in Bilbiie et al. (2012), and exit when hit by an exogenous exit shock. Firms grow by posting costly vacancies that are matched to unemployed workers. Once in the market, the size of a firm is determined by a downward-sloping demand curve.[1] As a result, ESAM features both an extensive margin of job creation and destruction. Households finance the entry of new firms on the stock market, along with the creation of physical capital. The price of both assets fluctuates endogenously in response to shocks. If employed, households choose how many hours to work.

In this context, an expansionary supply shock initially increases profits, which attracts new firms into the market. The resulting rise in the demand for labor by both incumbents and new entrants leads to a contraction in unemployment. This correlation pattern is consistent with the BVAR analysis

[1] Equivalently, we could assume decreasing returns to scale to determine the boundaries of firms, as pointed out by Bilal et al. (2022).

motivating our research.

We estimate the structural parameters of our model by matching the impulse responses obtained from our BVAR. To do so, we use a variant of the Bayesian minimum distance technique proposed by Christiano et al. (2010).[2] The VAR-based impulse response functions (IRFs) are identified with sign restrictions. Since IRFs identified with sign restrictions are set-identified, the minimum distance estimation follows the procedure outlined by Hofmann et al. (2012). Specifically, we consider a large set of VAR-based IRFs fulfilling the sign restrictions, and for each of them, we run a minimum distance estimation with the model-based IRFs. The technique delivers moments and quantiles of the implied posterior mode distributions of the estimated parameters. This approach leverages the information embedded in the estimation process to a greater extent than the more commonly used method that minimizes the distance from the median impulse response function.

To understand the role of frictional entry in the transmission of shocks, we consider a version of our model characterized by frictionless firm entry. In this case, our model reduces to a monopolistically competitive version of the standard search and matching model, which we refer to as the SAM model. We estimate the parameters of SAM using the same technique outlined above. We find that SAM delivers a counterfactual impact response of aggregate profits and hours to technology shocks. More precisely, while an expansionary technology shock leads on impact to higher profits and hours in the data, SAM implies a contraction. Since Shimer (2005), the capacity of SAM to replicate labor market dynamics in response to technology shocks has been questioned. Indeed, SAM displays large counterfactual cyclical swings in wages in response to technology shocks, which compress the profitability of firms and limit its ability to explain labor market variability. For the same reason, SAM displays the counterfactual impact responses of profits and aggregate hours to technology shocks that we identify in our analysis.

In ESAM, the interaction between the labor market and firm dynamics enhances intertemporal substitution in labor, leading to an endogenous form of wage moderation. The reason is that households have an additional asset to transfer resources intertemporally compared to SAM: investment in new firms. Since future firm profits are expected to be high in response to the

[2] A minimum distance technique to estimate the parameters of a SAM model is also adopted by Trigari (2009).

shock, households invest in the creation of new firms. To gather resources to invest, households substitute labor intertemporally more than they do in SAM. As a result of this intertemporal substitution, the response of the real wage is milder than in SAM. This form of endogenous wage moderation translates into a procyclical response of aggregate profits and hours to technology shocks, consistently with our VAR evidence.[3]

To support our intuition, we consider a version of SAM augmented with exogenous real wage rigidity, which is dubbed as WSAM. As expected, this rigidity prevents sharp cyclical swings in wages and helps account for the estimated economic response to shocks. However, by focusing on technology shocks, we show that while real wage rigidity improves SAM's ability to explain the responses of wages and profits, it leads to a response of job creation that does not align with the data. Furthermore, we show that the marginal likelihood of ESAM is substantially higher than that of both SAM and WSAM. [4]

In summary, ESAM outperforms both SAM and its version with real wage rigidity in explaining the joint response of profits, entry, hours worked, and job creation to exogenous shocks, while performing at least as well as those models in capturing fluctuations in unemployment and vacancies.

The remainder of the paper is structured as follows. Section 2 offers a brief review of the relevant literature. Section 3 presents the empirical evidence. Section 4 introduces our baseline model, ESAM. Section 5 describes the econometric methodology. Section 6 discusses the key findings, including the Bayesian estimation of the model's parameters and the model's impulse response functions (IRFs). Section 7 develops a New Keynesian extension of ESAM. Incorporating New Keynesian features further enhances ESAM's ability to replicate the dynamics of key macroeconomic variables over business cycles. The Appendix outlines SAM and its version with real wage rigidities. Technical details, robustness checks, and counterfactuals are provided in an online Appendix, which also includes detailed estimates for the New Keynesian versions of our model

[3]Intertemporal substitution of labor supply through capital accumulation is central to modern business cycle theories. Using U.S. household-level data, Saijo (2019) shows that stockholders increase their hours of work in response to an expansionary technology shock that positively affects stock returns.

[4]We do not rely on the ability to match the response of entry to shocks when estimating and comparing models using the marginal likelihood

2 Related Literature

A recent and growing literature, inspired by the work of Melitz (2003), Bilbiie et al. (2012), Clementi and Palazzo (2016), Jaimovich and Floetotto (2008), Clementi and Palazzo (2016), Etro and Colciago (2010), Hamano and Zanetti (2017), Rossi (2019) among others, studies how the extensive margin of firm entry and product variety can contribute to understanding the business cycle. These models endogenize the number of firms or varieties by relaxing the free entry condition, specifically by making the entry of new firms contingent on incurring a sunk cost. Bergin and Corsetti (2008) originally studied the monetary transmission mechanism in the presence of an extensive margin of investment in open economies, more recently Lewis and Poilly (2012), Bilbiie (2020), and Colciago and Silvestrini (2022) reconsidered the issue in closed economies. Fujita and Ramey (2003), and Coles and Moghaddasi Kelishomi (2018) examine the implications of breaking the free-entry condition in SAM by introducing fixed costs of creating vacancies. They argue that this improves the fit of SAM to unemployment and job creation data without resorting to wage stickiness. Our analysis is similar to theirs in this regard, but diverges in both the modeling approach and focus. In terms of modeling, we propose a framework where firm entry is frictional, and where a firm is not a job. Hence, job creation and vacancy creation are not equivalent. In terms of focus, we analyze to what extent our model can replicate the estimated responses of hours, profits, real wages, and entry to shocks commonly considered in the literature.

Close to this paper are contributions by Colciago and Rossi (2015), Cacciatore and Fiori (2016), Shao and Silos (2013), Schaal (2017), Mangin and Sedláček (2018), Kaas and Kimasa (2021) and Bilal et al. (2022), and Carrillo-Tudela et al. (2021). Schaal (2017) develops an equilibrium search-and-matching model with firm dynamics and heterogeneity in productivity and size. His model can replicate key features of the microeconomic behavior of firms. Additionally, he shows that uncertainty helps to explain a large fraction of the volatility of unemployment during recessions. Bilal et al. (2022) study labor reallocation in a framework with firm dynamics, a firm size distribution, and on-the-job search. They quantify the misallocation cost of frictions, and explain the failure of the job ladder during the Great Recession as a result of the collapse in firm entry. Our model neglects heterogeneity to show that a minimal perturbation to the SAM model, namely frictional firm entry, can rationalize the evidence about the correlation between total hours of work, firm profits and unemployment. Kaas and Kimasa (2021) consider a model with firm dynamics and search frictions in both product and labor markets. In their setting with heterogeneous firms, firms' employment responses to productivity shocks are weaker when firms are more demand-constrained. Colciago and Rossi (2015), Cacciatore and Fiori (2016) and Shao and Silos (2013) consider search and matching models with an extensive margin of investment. Colciago and Rossi (2015) and Mangin and Sedláček (2018) study the role of competition in the response of the labor share of income to technology shocks. Cacciatore and Fiori (2016) consider the macroeconomic effects of deregulating the goods and labor markets. Shao and Silos (2013) find that sunk costs of entry imply a countercyclical net present value of vacancies, which has implications for the surplus division between firms and workers over the business cycle. Carrillo-Tudela et al. (2021) develop and estimate a model of firm dynamics and on-the-job search over the business cycle. They show that firm job destruction is negatively correlated with cyclical unemployment, and that this correlation contributes to explaining the persistence of unemployment. Compared to these studies, this paper offers both empirical and theoretical contributions. We present empirical evidence on the joint responses of firm entry, profits, hours, and unemployment to shocks in technology, price markups, and the relative wage bargaining power of workers. We also develop versions of the ESAM model that incorporate various empirically relevant frictions. By disentangling the role of each friction in the transmission of shocks, we assess the statistical fit of each model variation.

Our paper is related to the work of Christiano et al. (2016) and Christiano et al. (2021), who stress the importance of wage inertia for the cyclicality of unemployment, vacancies and inflation. Christiano et al. (2016) develop a model where wage inertia emerges as the solution to the bargaining problem between firms and workers. Our paper, while maintaining standard Nash bargaining between firms and workers, obtains wage inertia thanks to the interaction between the asset market and the labor market.

3 Evidence

In this section, we estimate a Bayesian Structural Vector Autoregressive (BVAR) model to identify three distinct shocks: one that boosts aggregate productivity, one that lowers the price markup, and another that diminishes workers' wage bargaining power. Our goal is to present a set of stylized facts regarding the responses of entry, hours worked, profits, and labor market variables to these shocks. We assume Gaussian-inverse Wishart priors for the reduced-form VAR parameters. Endogenous variables in the VAR consist of $n = 11$ U.S. quarterly series: real GDP, real wages, real profits, unemployment rate, vacancies, total hours, inflation rate, labor productivity, firm entry, real consumption, and real investment in physical capital. Details about data sources and definitions are provided in the online Appendix. The sample period spans from 1960:Q1 to 2016:Q4. All series are considered in annual terms and, for those in levels, in per capita. Since the DSGE models we will adopt to explain the empirical results are stationary, we take deviations of the non-stationary time series from their respective trend by applying a one-sided Hodrick-Prescott filter to the logarithms of the series.[5] The benchmark VAR features two lags, as suggested by both Akaike and Bayesian information criterion. In the online Appendix, we comment on the battery of robustness checks for the VAR considering a i) larger number of lags, ii) different sample periods, iii) different filtering techniques, and iv) variables in log-levels.

The identification of the structural shocks is achieved by imposing sign restrictions on VAR-IRFs. Specifically, we implement the QR decomposition procedure proposed by Rubio-Ramirez et al. (2010).[6] All shocks are intended to increase real activity. To choose the set of restrictions, we rely on well established results in the literature.

The set of restrictions to VAR-IRFs are imposed only at the impact period, with two exceptions. The sign of the responses of labor productivity and inflation to technology shocks are restricted for 20 and 4 periods, respectively. Similar restrictions are imposed by Dedola and Neri (2007), Fujita (2011),

[5]As pointed out by Born and Pfeifer (2014), using a one-sided, i.e. "causal" filter in Stock and Watson (1999), guarantees that the time ordering of the data is not disturbed and the autoregressive structure is preserved.

[6]Technical details about the identification procedure are left to the online Appendix.

Peersman (2005) and Hofmann et al. (2012). [7] Table 1 summarizes the set of restrictions we impose. A question mark indicates no restriction.

	Shock		
Variable	*Technology*	*Price markup*	*Workers bargaining power*
Real GDP	?	> 0	> 0
Real wages	> 0	> 0	< 0
Real profits	> 0	< 0	> 0
Firm entry	> 0	?	> 0
Labor productivity	> 0	?	?
Inflation	< 0	< 0	< 0

Table 1: Sign restrictions for the identification of structural shocks in the VAR model. All restrictions last for the impact period, but for the labor productivity (20 periods) and inflation (4 periods) to the technology shock.

We identify an expansionary technology shock by imposing that it leads to an increase in labor productivity, real wage, real profits, firm entry, and to a reduction in inflation. [8] Shocks that weaken the relative bargaining power of workers are expansionary since they reduce labor market distortions. We distinguish them from expansionary technology shocks by imposing that they lead to a reduction in the real wage. The reduction in the real wage is also assumed to result in lower inflation.[9] Shocks that weaken the ability of firms to price above marginal costs, i.e. price markup shocks, expand output by reducing distortions in the product markets. A shock that decreases the price markup, is distinguished from an expansionary technology shock by assuming that it affects negatively profits, while it is distinguished from a shock to the bargaining power of workers by assuming that it has both a positive impact on the real wage and a negative impact on profits.[10] The responses

[7] Reducing the number of periods over which we restrict the response of labor productivity to technology shocks does not alter our findings.

[8] Although the technology shocks we identify are meant to increase real activity, we are agnostic and parsimonoius in selecting restrictions, and choose to leave unconstrained the response of real GDP. We verified that adding a positive sign to the response of real GDP would have a negligible effect on IRFs, since GDP reacts positively for almost all the draws, i.e. at the 90^{th} percentile, even if no restrictions are imposed.

[9] The identification strategy is consistent with that in Foroni et al. (2018), who identify a shock that reduces the bargaining power of workers in a small VAR model by imposing an increase in GDP, and a decline in the real wage and in prices. The aforementioned authors distinguish a wage bargaining power shock from a labor supply shock assuming that unemployment falls in response to the former. Although unrestricted in our exercise, we find that unemployment similarly decreases.

[10] The restrictions on the responses of GDP, real wages, and real profits to markup shocks are consistent with those imposed, *inter alia*, by Bergholt et al. (2019), who study shocks to the elasticity of substitution among goods in a small VAR model. Indeed in a monopolistically competitive setting, changes in the

of unemployment, vacancies, total hours, investment, and consumption are never constrained.

In the online Appendix we assess the robustness of the sign restrictions we imposed. The first battery of tests evaluates the robustness of the positive signs we imposed on profits and entry in response to technology shocks. To do so, we identify technology shocks using alternative VAR specifications with respect to the baseline, and alternative identification strategies. Among the latter, we use the long-run approach proposed by Gali (1999), whereby a neutral technology shock is identified assuming that it is the only shock to have long-run effects on labor productivity. Also, we use the approach by Francis et al. (2014), whereby the neutral technology shock is identified as the one which maximizes the forecast error variance share of labor productivity in the long run. The online Appendix details the approaches used to identify the effects of technology shocks on entry and profits. All the robustness tests we carry out support the sign restrictions we impose: in response to an expansionary technology shock, entry and profits increase for several periods.

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elasticity of substitution lead to markup variations. Additionally, the restrictions imposed on GDP, real profits, and inflation to identify a markup shock are consistent with the findings in Lewis and Stevens (2015), who estimate a business cycle model with firms' entry using US quarterly data over the period 1954Q4–1995Q2.

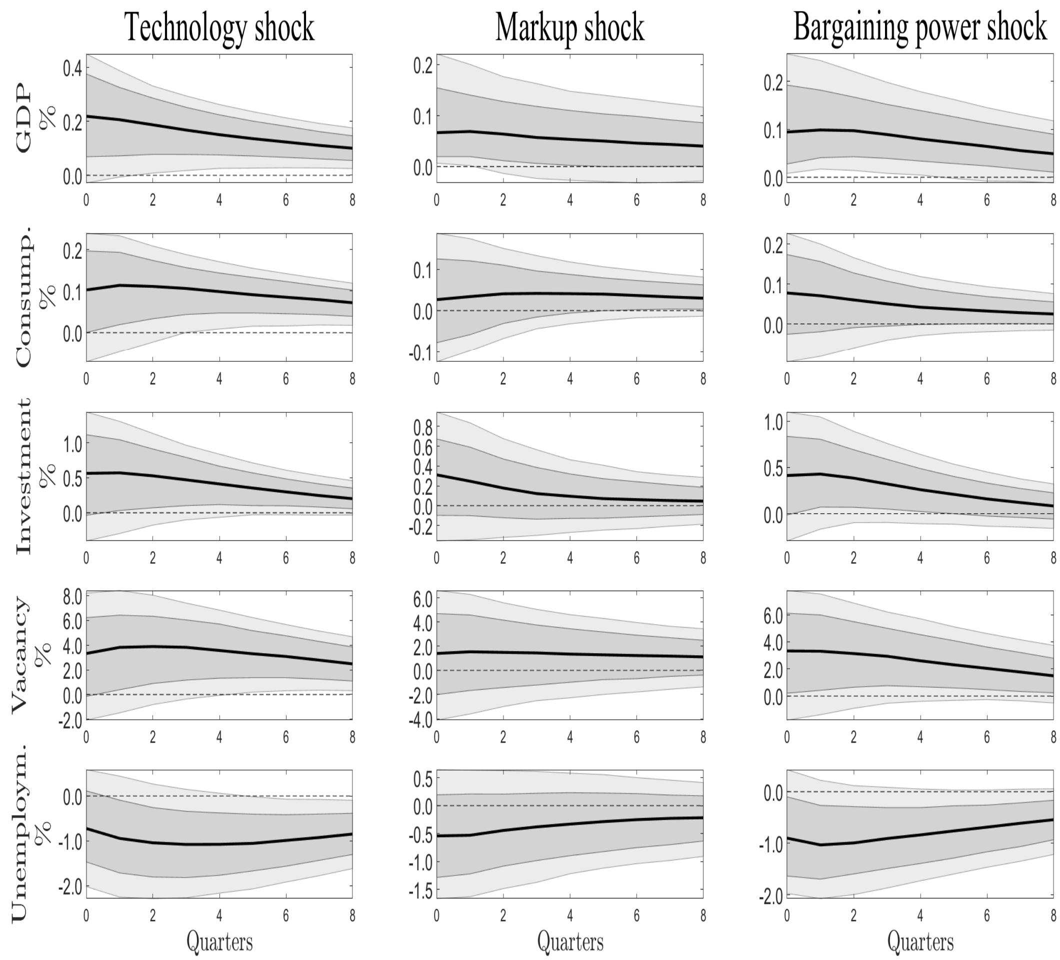

Figure 1: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage).

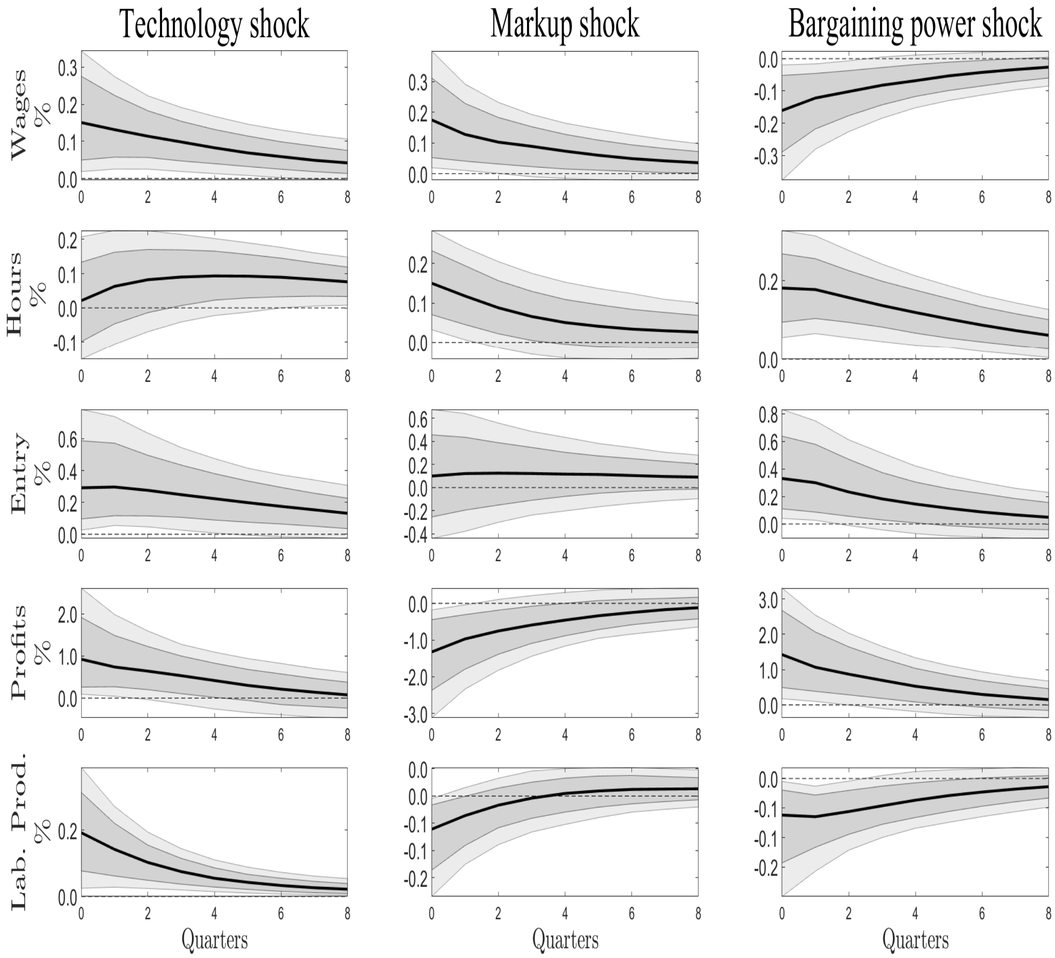

Figure 2: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage).

Shaded areas in Figure 1 and Figure 2 show the 90% (light grey) and 68% (dark grey) percentile of credible intervals of the VAR-IRFs to the three identified structural shocks. The figures also show the median of the posterior distributions of the impulse responses (black solid lines).[11] The results suggested by Figure 1 are standard in the VAR literature. Expansionary supply shocks lead to a positive comovement between output, investment in physical capital, and consumption. At the same time, we observe a negative comovement between vacancies, which rise, and the unemployment rate, which persistently decreases. Figure 2, instead, presents some new results about the joint response of entry, hours, real wage, and profits to the shocks we identified. First, the positive response of profits to expansionary technology shocks and to shocks that reduce the bargaining power of workers is associated with a rise in entry of new firms and aggregate hours of work. Shocks that reduce the price markup and profits are associated with considerable uncertainty in the response of firm entry, suggesting that profits are a driver of business creation. Aggregate hours of work rise in response to expansionary shocks, although there is a sizeable uncertainty in the impact response of hours to technology shocks. Labor productivity responds negatively to price markup and workers' wage bargaining power shocks.[12]

The evidence suggests that in response to expansionary supply shocks, we should anticipate a positive correlation between firm entry, profits, and hours of work. To capture these characteristics of U.S. data, we propose a model that includes endogenous frictional firm entry and monopolistic competition in the goods market within a framework exhibiting search and matching frictions in the labor market.

[11] To maintain consistency with the DSGE analysis, we report the VAR-based responses only for real variables. The response of inflation, which is constrained on impact for the three shocks, is provided in the online Appendix along with other robustness checks.

[12] In the online Appendix, we also run additional tests to verify the robustness of the empirical findings across different VAR specifications. First, we increase the number of lags. Second, we change the length of the sample period to exclude, in one case, the Great Recession, in another, the period prior to the Great Moderation, and lastly, both periods. Third, we detrend the data using the two-sided Hodrick-Prescott filter to the logarithms of the series. Fourth, we consider variables in log-levels and use linear and quadratic time trends. Remarkably, the empirical findings are robust across all specifications.

4 The Model Economy: ESAM

In this section we outline ESAM, our benchmark economy. It embeds frictional firm entry in a SAM model with large firms. To make the model estimable, following Christiano et al. (2005) and Trigari (2009), we consider habit persistence in consumption, physical capital to produce the final goods and adjustment costs at the intensive margin of investment. As in Casares et al. (2018) and Lewis and Poilly (2012), we include a form of adjustment costs along the extensive margin of investment. The economy features monopolistic competition in the markets for final goods. Goods are imperfect substitutes for each other, and are aggregated into a final good through a CES aggregator. As a result, firms face a downward-sloping demand curve that determines their size, and price with a markup over marginal costs. Households use the final good for consumption and investment purposes.

4.1 Labor and Goods Markets

At the beginning of each period, a mass N_t^e of new firms enters the market, while at the end of the period a mass $\delta \in (0,1)$ of market participants exits from the market for exogenous reasons. As a result, the mass of firms, N_t, follows the law of motion:

$$N_{t+1} = (1-\delta)\left(N_t + N_t^e\right),$$

Following Bilbiie et al. (2012), we assume that new entrants at time t will only start producing at time $t+1$ and that the exit rate, δ, is independent of the period of entry and constant over time. The assumption of an exogenous constant exit rate in adopted for tractability, but it also has empirical support. Using U.S. annual data on manufacturing, Lee and Mukoyama (2015) find that, while the entry rate is procyclical, annual exit rates are similar across booms and recessions. Below we describe the entry process in detail.

The labor market is characterized by search and matching frictions, as in Andolfatto (1996) and Merz (1995). Producers post vacancies in order to hire new workers. Unemployed workers and vacancies combine according to a constant returns to scale matching function and deliver m_t new hires, or matches, in each period. The matching function reads as:

$$m_t = \gamma_m \left(v_t^{tot}\right)^{1-\gamma} u_t^{\gamma},$$

where γ_m reflects the efficiency of the matching process, v_t^{tot} is the total number of vacancies created at time t and u_t are the workers searching for a job.[13] The probability that a firm fills a vacancy is given by $q_t = \frac{m_t}{v_t^{tot}}$, while the probability to find a job for an unemployed worker reads as $z_t = \frac{m_t}{u_t}$. Firms and individuals take both probabilities as given. Matches become productive in the same period in which they are formed. Each firm separates exogenously from a fraction $1 - \varrho$ of existing workers each period, where ϱ is the probability that a worker stays with a firm until the next period. As a result, a worker may separate from a job for two reasons: either because the firm where the job is located exits the market or because the match is destroyed. Since these sources of separation are independent, the evolution of aggregate employment, L_t, is given by:

$$L_t = (1 - \delta)\,\varrho L_{t-1} + m_t.$$

4.2 Firms and Technology

The final good is produced aggregating a continuum of measure N_t of differentiated goods according to the function

$$Y_t = N_t^{\frac{1}{\varepsilon_t - 1}} \left(\sum_{z=1}^{N_t} y_t(z)^{\frac{\varepsilon_t - 1}{\varepsilon_t}} \right)^{\frac{\varepsilon_t}{\varepsilon_t - 1}}, \tag{1}$$

where $y_t(z)$ is the production of the individual good z, and $\varepsilon_t > 1$ is the elasticity of substitution between goods.[14] The latter is assumed to follow an AR(1) process with coefficient ρ_ε. Each firm z produces a differentiated good with the following production function

$$y_t(z) = A_t \left[n_t(z)\, h_t(z) \right]^{1-\alpha} k_{t-1}^{\alpha}(z), \tag{2}$$

where A_t represents technology which is common across firms and evolves exogenously over time following an AR (1) process with persistency ρ_a and standard deviation σ_a.Variable $n_t(z)$ is firm z's time t workforce, $h_t(z)$ represents hours per employee, and $k_{t-1}(z)$ is the stock of capital used by firm z at time t. Denoting with $p_t(z)$ the nominal price of good z, real profits of

[13] Given that population is normalized to one, the mass of unemployed workers and the unemployment rate are identical.

[14] The term $N_t^{-\frac{1}{\varepsilon - 1}}$ implies that there is no variety effect in the model.

a firm at time t can by defined as

$$\pi_t(z) = \frac{p_t(z)}{P_t} y_t(z) - w_t(z) h_t(z) n_t(z) - r_t^k k_{t-1}(z) - \kappa v_t(z), \tag{3}$$

where $w_t(z)$ is the real wage paid by firm z, $v_t(z)$ represents the number of vacancies posted at time t, and κ is the output cost of keeping a vacancy open. The value of a firm is the expected discounted value of its future profits

$$V_t(z) = E_t \sum_{s=t+1}^{\infty} \Lambda_{t,s} \pi_s(z), \tag{4}$$

where $\Lambda_{t,t+1} \equiv (1-\delta) \beta \frac{\lambda_{t+1}}{\lambda_t}$ is the households' stochastic discount factor which takes into account that firms' survival probability is $1-\delta$. Firms which do not exit the market have a time t individual workforce given by

$$n_t(z) = \varrho n_{t-1}(z) + v_t(z) q_t. \tag{5}$$

The demand faced by the producer of each variant is

$$y_t(z) = \left(\frac{p_t(z)}{P_t} \right)^{-\varepsilon_t} \frac{Y_t}{N_t}, \tag{6}$$

where P_t is defined as

$$P_t = N_t^{\frac{1}{\varepsilon_t - 1}} \left[\sum_{z=1}^{N_t} (p_t(z))^{1-\varepsilon_t} \right]^{\frac{1}{1-\varepsilon_t}}. \tag{7}$$

4.3 Pricing and Job creation

In what follows we distinguish firms according to their period of entry. We define as new entrants those firms which enter the market in t and, if not hit by an exit shock, will start producing in $t+1$. New firms are those which entered the market in period $t-1$ and in period t produce for the first time. New firms are thereby the fraction of time $t-1$ entrants which survived to the next period.[15] We define incumbent producers as those firms which entered the market in period $t-2$, or prior. The distinction is relevant because

[15] Notice that N_{t-1}^e are the entrants at time $t-1$, and that just a fraction $(1-\delta)$ of time $t-1$ entrants start producing in period t. We define these firms as new firms.

new firms have no beginning of period workforce. Nevertheless, all firms producing in a given period t, independently of the period of entry, have in equilibrium the same size, impose the same markup over a common marginal cost, have the same individual level of production and the same value.[16] For this reason in what follows we drop the index z denoting variables relative to the individual firm. Optimal pricing implies that the relative price chosen by firms is

$$p_t = \mu_t mc_t, \tag{8}$$

where mc_t are real marginal costs, and μ_t defines the price markup. To maintain comparability with the bulk of the literature, ESAM features monopolistic competition *à la* Dixit and Stiglitz (1977). In this case, the price markup assumes the traditional form

$$\mu_t = \frac{\varepsilon_t}{\varepsilon_t - 1}. \tag{9}$$

As well known, the price markup, μ_t, is decreasing in the degree of substitutability between products, ε_t. We assume that the latter follows an AR (1) process with persistency ρ_ε and standard deviation σ_ε. A firm will hire workers up to the point where the value of the marginal worker, defined as ϕ_t, equals its marginal cost, that is when

$$\phi_t = \left((1-\alpha) \left(\frac{A_t}{\mu_t} \right) \left(\frac{k_{t-1}}{n_t h_t} \right)^\alpha h_t - w_t h_t \right) + \varrho E_t \left[\Lambda_{t,t+1} \phi_{t+1} \right]. \tag{10}$$

Condition (10) implies that the value of the marginal worker, ϕ_t, is represented by the profits associated to the additional worker, the term in brackets, plus the continuation value. Next period, with probability ϱ, the match is not severed. In this event, the firm obtains the future expected value of a job. Similarly, a firm will post vacancies such that the value of the marginal worker, ϕ_t, equals to the expected cost of hiring the worker, $\frac{\kappa}{q_t}$. Formally the vacancy posting condition is:

$$\phi_t = \frac{\kappa}{q_t}, \tag{11}$$

where κ defines the cost of opening a vacant position in term of the final good. Combining equations (10) and (11) delivers the Job Creation Condition

[16] See the online Appendix for a formal proof.

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$$\frac{\kappa}{q_t} = \left((1-\alpha) \left(\frac{A_t}{\mu_t} \right) \left(\frac{k_{t-1}}{n_t h_t} \right)^{\alpha} h_t - w_t h_t \right) + \varrho E_t \left[\Lambda_{t,t+1} \frac{\kappa}{q_{t+1}} \right], \tag{12}$$

where the pricing condition was used to substitute for the real marginal cost, namely $mc_t \equiv \frac{MC_t}{P_t} = \frac{1}{\mu_t}$.

4.4 Hiring policy

Let π_t^{new} and v_t^{new} be, respectively, the real profits and the number of vacancies posted by a new firm. Symmetrically, π_t and v_t define the individual profits and vacancies posted by an incumbent producer. New firms and incumbent firms are characterized by the same size, n_t. Thus, the optimal hiring policy of new firms, which have no initial workforce, consists in posting at time t as many vacancies as required to hire n_t workers. As a result $v_t^{new} = \frac{n_t}{q_t}$. Since $n_t = \varrho n_{t-1} + v_t q_t$, it has to be the case that

$$v_t^{new} = v_t + \frac{\varrho n_{t-1}}{q_t}. \tag{13}$$

Hence, a new firm posts more vacancies than an incumbent producer. For this reason, and given vacancy posting is costly, the profits of new firms are lower than those of incumbent firms. To see this, notice that

$$\pi_t^{new} = y_t - w_t h_t n_t - r_t^k k_{t-1} - \kappa v_t^{new}. \tag{14}$$

Substituting equation (13) in the latter delivers

$$\pi_t^{new} = \left(y_t - w_t h_t n_t - r_t^k k_{t-1} - \kappa v_t \right) - \kappa \frac{\varrho n_{t-1}}{q_t} = \pi_t - \kappa \frac{\varrho n_{t-1}}{q_t}. \tag{15}$$

The last equality follows from the fact that the term in the round bracket represents the profits of an incumbent producer, π_t. Consistently with the U.S. empirical evidence in Haltiwanger et al. (2013) and Cooley and Quadrini (2001), a young firm creates on average more new jobs than a mature firm and distributes lower dividends.

4.5 Households

Using the family construct of Merz (1995), the representative household consists of a continuum of individuals of mass one. Members of the household insure each other against the risk of being unemployed. The representative family has lifetime utility:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left(\ln \left(C_t - \vartheta C_{t-1} \right) - \chi L_t \frac{{h_t}^{1+\varphi}}{1+\varphi} \right) \quad \chi, \eta, \varphi \geq 0, \tag{16}$$

where $\beta \in (0,1)$ is the discount factor, the variable h_t represents individual hours worked by each member of the household, and C_t is the consumption of the final good. Consumption displays internal habit persistence of degree ϑ. The household allocates his or her savings between stocks or physical capital. Following the production and sales of varieties in the imperfectly competitive goods markets, the stock ownership entails a distribution of dividends to the households. As a result, the representative agent enjoys capital, dividend, and, if employed, labor income. Markets are complete. Unemployed individuals receive a real unemployment benefit b, hence the overall benefit for the household is $b\left(1 - L_t\right)$. This is financed through lump sum taxation by the Government. Notice that the household recognizes that employment is determined by the flows of its members into and out of employment according to:

$$L_t = \left(1 - \delta\right) \varrho L_{t-1} + z_t u_t. \tag{17}$$

Timing of investment in the stock market is as in Bilbiie et al. (2012) and Chugh and Ghironi (2011). At the beginning of period t, the household owns shares of two portfolios of assets. Specifically the households owns x_t shares in the portfolio of incumbent firms, and x_t^e shares of a portfolio of new firms, each of which has value V_t. As a result the total value of stock holdings at time t is $\left(1 - \delta\right) V_t \left[N_{t-1} x_t + N_{t-1}^e x_t^e\right]$.[17] During period t, the household purchases shares in two mutual funds to be carried into period $t+1$. The first mutual fund represents the ownership of the N_t incumbents in the market in period t. The household also finances the entry of N_t^e new entrants by acquiring x_{t+1}^e shares in an another fund which includes just newly created firms.[18]

[17] We prove in the next section that time t-1 entrants have, at time t, the same value as incumbents.

[18] All firms, new entrants and incumbents, have the same probability of exit. For this reason households finance both, the continuing operations of incumbents, and invest in new entrants.

The household is assumed to own physical capital, K_t, which accumulates according to the following law of motion:

$$K_t = (1-\delta^k)K_{t-1} + \left[1 - \frac{\phi_I}{2}\left(\frac{I_t^k}{I_{t-1}^k} - 1\right)^2\right] I_t^k, \tag{18}$$

where I_t^k denotes gross investment, and δ^k is a parameter denoting the rate of depreciation of physical capital. The term in brackets introduces investment adjustment costs as in Christiano et al. (2005). The assumed functional form implies the absence of adjustment costs up to first order in the vicinity of the deterministic steady state.

The budget constraint of the representative household can be written as

$$\begin{gathered} C_t + V_t N_t x_{t+1} + V_t^e N_t x_{t+1}^e + I_t^k = \\ w_t h_t L_t + b\left(1 - L_t\right) + r_t^k K_t + \left(1-\delta\right)\left[\pi_t + V_t\right] N_{t-1} x_t + \left(1-\delta\right)\left[\pi_t^e + V_t\right] N_{t-1}^e x_t^e - T_t \end{gathered} \tag{19}$$

where $(1-\delta)\left(\pi_t N_{t-1} x_t + \pi_t^e N_{t-1}^e x_t^e\right)$ are profits distributed to households, as stock owners. Besides profits, the family receives real labor income $w_t h_t L_t$, where w_t is the real wage, and capital income $r_t^k K_t$, where r_t^k is the real rental rate per unit of capital. Unemployed members of the households receive an unemployment subsidy equal to b in real terms, which is financed through lump sum taxes, denoted by T_t. As a result, the overall benefit for the household equals $b\left(1 - L_t\right)$. The household chooses how much to save in physical capital and in the creation of new firms through the stock market according to standard Euler and asset pricing equations.[19] The first order condition (FOC) with respect to employment, L_t, is:

$$\Gamma_t = \lambda_t w_t h_t - \chi \frac{h_t^{1+\varphi}}{1+\varphi} - b\lambda_t + \beta E_t\left[\left(\left(1-\delta\right)\varrho - z_{t+1}\right)\Gamma_{t+1}\right], \tag{20}$$

where Γ_t is the marginal value to the household of having one member employed rather than unemployed, and λ_t is the marginal utility of consumption. Equation (20) indicates that the household's shadow value of one additional employed member (the left hand side) has four components: first, the increase in utility generated by having an additional member employed, given by the real wage expressed in utils; second, the decrease in utility due to more hours dedicated to work, given by the marginal disutility of employment; third the foregone utility value of the unemployment benefit $b\lambda_t$; fourth, the continua-

[19] To lighten the reading, we report asset pricing equations in the online Appendix.

tion utility value, given by the contribution of a current match to next period household's employment.

4.6 Endogenous Entry

In each period the level of entry is determined endogenously to equate the value of a new entrant, V_t^e, to the entry cost

$$V_t^e = \psi_t. \tag{21}$$

The latter is composed by a constant term, ψ_0, and by a term which is related to market congestion externalities, $\psi_1 \left(\frac{N_t^e}{N_t}\right)^{\varsigma}$, as in Casares et al. (2018). In formula, entry costs read as

$$\psi_t = \psi_0 + \psi_1 \left(\frac{N_t^e}{N_t}\right)^{\varsigma}. \tag{22}$$

A higher rate of entry, $\frac{N_t^e}{N_t}$, implies an increase in the costs of creating a new firm. The non-constant, state dependent term in the entry cost function can be interpreted as an adjustment cost to extensive margin of investment akin to the cost of adjusting investment in physical capital.

Notice that perspective new entrants have lower value than incumbents because they will have, in case they do not exit the market before starting production, to set up a workforce in their first period of activity. The difference in the value between a firm which is already producing and a perspective entrant is, in fact, the discounted value of the higher vacancy posting cost that the latter will suffer, with respect to the former, in the first period of activity. Formally,

$$V_t = V_t^e + \kappa \varrho E_t \Lambda_{t,t+1} \frac{n_t}{q_{t+1}}, \tag{23}$$

where V_t is the time t value of an incumbent firm.

4.7 Bargaining over Wages and Hours

As in Trigari (2009), individual bargaining takes place along two dimensions: the real wage and hours of work. We assume Nash bargaining. That is, the firm and the worker choose the wage w_t and the hours of work h_t to maximize the Nash product

$$(\phi_t)^{1-\eta_t}\left(\frac{\Gamma_t}{\lambda_t}\right)^{\eta_t}, \tag{24}$$

where ϕ_t is firm value of having an additional worker, while Γ_t/λ_t is the household's surplus expressed in units of consumption.[20] The parameter η_t reflects the parties' relative bargaining power. We assume that the latter follows an AR(1) process with persistency ρ_η, and standard deviation σ_η. The FOC with respect to the real wage is

$$\eta_t\phi_t = (1-\eta_t)\frac{\Gamma_t}{\lambda_t}. \tag{25}$$

Substituting in the latter the definition of ϕ_t in equation (10), and that of Γ_t in equation (20), we obtain the wage equation

$$w_t h_t = \eta_t (1-\alpha)\left(\frac{A_t}{\mu_t}\right)\left(\frac{k_{t-1}}{n_t h_t}\right)^{\alpha} h_t + (1-\eta_t)\left(\frac{\chi}{\lambda_t}\frac{h_t^{1+\varphi}}{1+\varphi} + b\right) + \eta_t\beta\kappa E_t\left[\frac{\eta_{t+1}}{\eta_t}\frac{1-\eta_t}{1-\eta_{t+1}}\frac{\lambda_{t+1}}{\lambda_t}\theta_{t+1}\right], \tag{26}$$

where $\theta_t = \frac{z_t}{q_t}$ measures the tightness in the labor market. The wage shares costs and benefits associated to the match according to the extent of the bargaining power, as measured by η_t. The worker is rewarded for a fraction η_t of the firm's revenues and savings of hiring costs, and compensated for a fraction $1-\eta_t$ of the disutility he suffers from supplying labor and the foregone unemployment benefits. Individual hours, h_t, are such that

$$\frac{\chi}{\lambda_t}h_t^{\varphi} = (1-\alpha)^2\left(\frac{A_t}{\mu_t}\right)\left(\frac{k_{t-1}}{n_t h_t}\right)^{\alpha}. \tag{27}$$

Because the firm and the worker bargain simultaneously about wages and hours, the outcome is (privately) efficient and the wage does not play an allocational role for hours.[21]

[20] Notice that the vaue of an additional worker is identical for all firms. Thus the wage paid by incumbents and new firms is identical. Brown and Medoff (2003) find that, when controlling for worker characteristics, there is no statistically significant relationship between firms' age and wages.

[21] Notice that we ruled out the possibility of a hiring externality. This simplifies the derivation of the wage equation. Ebell and Haefke (2009) show that the quantitative effect of overhiring is minor.

4.8 Aggregation and Market Clearing

The mass of firms evolves according to:

$$N_{t+1} = (1-\delta)\left(N_t + N_t^e\right). \tag{28}$$

The firms' individual workforce, n_t, is identical across producers, hence it reads as $L_t = N_t n_t$. The aggregate production function is:

$$Y_t = N_t y_t = A_t \left(L_t h_t\right)^{1-\alpha} K_{t-1}^{\alpha}. \tag{29}$$

Total vacancies posted in period t are $v_t^{tot} = (1-\delta) N_{t-1} v_t + (1-\delta) N_{t-1}^e v_{t-1}^{new}$, where $(1-\delta) N_{t-1}$ is the mass of incumbent producers, and $(1-\delta) N_{t-1}^e$ is the mass of new firms. Aggregating the budget constraints of households, and considering that $T_t = b(1-L_t)$, the implied aggregate resource constraint of the economy is

$$C_t + \psi_t N_t^e + I_t^k = w_t h_t L_t + r_t^k K_{t-1} + PRO_t, \tag{30}$$

which states that the sum of consumption, extensive investment and intensive investment must equal the sum between labor income, capital income and aggregate profits, PRO_t, distributed to households at time t. Aggregate profits are defined as

$$PRO_t = (1-\delta) N_{t-1} \pi_t + (1-\delta) N_{t-1}^e \pi_t^{new}. \tag{31}$$

Goods' market clearing requires

$$Y_t = C_t + \psi_t N_t^e + I_t^k + \kappa v_t^{tot}. \tag{32}$$

The GDP is therefore defined as the total output net of the vacancy costs, namely

$$GDP_t = Y_t - \kappa v_t^{tot}. \tag{33}$$

Finally, the dynamics of aggregate employment reads as

$$L_t = (1-\delta)\varrho L_{t-1} + q_t v_t^{tot} \tag{34}$$

which shows that workers employed by a firm which exits the market join the mass of unemployed. The online Appendix lists all equilibrium conditions.

5 Bringing the Model to the Data

In this section, we describe the econometric methodology that we use to estimate the parameters of ESAM. The econometric technique that is particularly suited for our shock-based analysis is one that matches the impulse response functions estimated by our BVAR with the corresponding objects in the model. Section 5.1 outlines the Bayesian minimum distance procedure we follow to estimate the structural parameters of the model. Section 5.2 describes the prior distributions for the parameters to be estimated. Section 5.3 explains the calibration strategy for the remaining parameters. In order to assess the contribution of frictional firm entry to shaping the economy dynamics, we compare the predictions of ESAM with those of two alternative models. The first one is a SAM model with frictionless entry, which we obtain from ESAM by assuming away costly entry. We will refer to this model simply as SAM. All other features, such as frictions and parameters, are kept unchanged across SAM and ESAM. The second model is obtained by augmenting SAM with real wage rigidities. Following Shimer (2005) and Hall (2005), we model real wage rigidity in the form of a backward-looking social norm with parameter ϕ_w. The latter parameter reflects the degree of real wage rigidity: $\phi_w = 1$ implies a fixed real wage, while $\phi_w = 0$ corresponds to the case of Nash bargaining with flexible wages. We will refer to this model specification as WSAM. For reference, the Appendix provides analytical details concerning both SAM and WSAM.

5.1 Bayesian minimum distance estimation

We estimate the parameters in ESAM, SAM, and WSAM via Bayesian minimum distance techniques in the spirit of Christiano et al. (2010). Differently from the aforementioned authors, our VAR-IRFs are identified with sign restrictions. In this case, shocks are only set-identified. As a result, any of the VAR-IRFs satisfying the sign restrictions could be taken as the empirical counterpart to perform the minimum distance estimation. To tackle this issue, we follow Hofmann et al. (2012). We take a large set of VAR-IRFs satisfying the restrictions, namely 1000, and for each of them, we run Bayesian minimum distance estimation with the corresponding DSGE-IRFs.[22] The es-

[22] Any of the VAR-irfs and DSGE-irfs are stacked vectors, which in our case have dimension 15, the impulse responses horizon, times 3, the number of identified structural shocks, times 11, the number of endogenous

timation consists in optimizing over the posterior mode of the parameters in the vector θ, which contains the parameters to be estimated.[23] The procedure delivers 1000 vectors of posterior modes for the structural parameters in θ.

The most common approach in the literature is to take the vector of point-wise posterior medians of the structural impulse responses, or the response function closest to the posterior median (Fry and Pagan (2011)), as a measure of the central tendency of the impulse response functions. The latter then serves as the empirical counterpart in the estimation of the model's structural parameters. We opt for the approach proposed by Hofmann et al. (2012), which avoids collapsing the VAR responses into the median, because it allows taking into account the full range of admissible structural models. By taking into account the complete set of plausible models, we ensure that no information about the diversity of structural responses is lost. This approach is motivated by the critiques raised by Inoue and Kilian (2013) and Kilian and Murphy (2014), who show that the posterior median response may not represent the most likely response in sign-identified VAR models.

However, given the wide range of admissible structural VAR models, it is computationally prohibitive to estimate the full posterior distribution of the structural DSGE model for each of them. Instead, we focus on estimating the posterior mode of the structural parameters for each of the 1,000 impulse response functions that meet the specified sign restrictions in the VAR. This method effectively balances the need to retain detailed information from the data with the practicality of estimation. Once we have the vectors of posterior modes, we assess the statistical fit of the estimated models using the marginal likelihood and calculate DSGE impulse response functions (IRFs) for the three key shocks of interest. The marginal likelihood is computed using a Laplace approximation around the posterior mode.[24] The DSGE-IRFs

variables we match.

[23]The optimization is run using Dynare 4.4.3, and Chris Sims' *csminwel* as maximization routine. Our programming codes modify the codes used in Christiano et al. (2010). We are grateful to Mathias Trabandt for sharing with us the original codes.

[24]Inoue and Shintani (2018) establish the consistency of the model selection criterion based on the marginal likelihood obtained from Laplace-type estimators. Methods like Laplace approximation and Geweke (1999)'s modified harmonic mean procedure are widely used in the literature to calculate the marginal likelihood. However, the former has a large advantage over the latter in terms of computational costs. This is so since in order to compute the marginal likelihood it requires only the posterior mode, and not a Metropolis-Hastings-based sample of the posterior distribution. For this reason, we follow Smets and Wouters (2007) and compare the alternative models we consider using the marginal likelihood computed with a Laplace approximation method.

are generated by informing the models with a vector of posterior modes at a time. We iterate over the vectors of posterior models and, for each model, we derive three distributions, namely: i) the distribution of posterior modes of the structural parameters; ii) the distribution of marginal likelihoods, and iii) the distribution of DSGE-IRFs. In the following analysis, we will use these distributions (i-iii) to evaluate the relative performance of the alternative models considered. The set of VAR-IRFs used for minimum distance estimation are: GDP, wages, profits, consumption, investment, all in real terms, total hours worked, unemployment rate, vacancies, and labor productivity. Since neither SAM nor WSAM feature an extensive margin of investment, we never use the VAR-IRF of new entrants in the estimation procedure. This allows for a fair comparison across models.

5.2 Prior distributions

The structural parameters we estimate, i.e. the elements of the vector θ, are the autoregressive parameters of the exogenous processes, ρ_a, ρ_ε, ρ_η, the standard deviations of shocks, σ_a, σ_ε, σ_η, the elasticity of the marginal disutility of labor, φ, the degree of internal habit in consumption, ϑ, the elasticity of the matching function, γ, the steady state value of the wage bargaining power of workers, η, the implied steady state replacement ratio, $rr \equiv \left(\frac{\chi}{\lambda}\frac{h^{1+\varphi}}{1+\varphi} + b\right)\frac{1}{w}$, the steady state value of the elasticity of substitution in the goods market, ε, and the quadratic investment adjustment cost parameter, ϕ_I.

We assume a Beta distribution with mean 0.01 for the standard deviation of the shocks, and an Inverse Gamma with mean 0.5 for the autoregressive parameters. The prior mean for the elasticity of the marginal disutility of labor is 2, while that for the degree of habit persistence is 0.6, in line, among others, with Boldrin et al. (2001). Following standard parameterization strategies of search and matching models, we set the prior means of the elasticity of the matching function and the steady state value of the workers' bargaining power to 0.5. In our model, the replacement ratio includes, both, the pecuniary unemployment benefit and the utility value of leisure. For this reason, we set its prior mean to 0.8. The prior mean for the elasticity of substitution among goods is set to 4.3, in line with the calibration strategy used in the literature and close to Ghironi and Melitz (2005) and Bilbiie et al. (2012). The investment adjustment cost is set to 4, consistently with Smets and Wouters (2007). In the case of ESAM, θ also includes the elasticity of entry costs to congestion externalities, ψ_1. We set its prior mean to 2 following Casares et al. (2018). In the case of WSAM, that is the SAM model featuring real wage rigidities, θ includes the persistence parameter characterizing the wage norm, γ_w, which has a prior mean equal to 0.8, consistently with the estimates by Christiano et al. (2016). Table 2, lists estimated parameters along with the assumed prior distributions.

Parameter	**Density**	**Mean**	**Std**	**Parameter**	**Density**	**Mean**	**Std**
ρ_a	*Beta*	0.8	0.1	φ	*Gamma*	2	0.4
ρ_ε	*Beta*	0.8	0.1	rr	*Beta*	0.7	0.05
ρ_η	*Beta*	0.8	0.1	ε	*Gamma*	4.3	0.75
σ_a	*Inv.Gamma*	0.01	0.05	η, γ	*Beta*	0.5	0.05
σ_ε	*Inv.Gamma*	0.01	0.05	ϕ_I	*Gamma*	4	0.75
σ_η	*Inv.Gamma*	0.01	0.05	ς	*Gamma*	2	0.2
ϑ	*Beta*	0.6	0.1	γ_w	*Beta*	0.8	0.05

Table 2: Prior distributions for DSGE structural parameters

5.3 Calibrated parameters

A subset of the structural parameters is not estimated, but calibrated. The time period is a quarter, and calibration follows Shimer (2005) and Blanchard and Galí (2010), among others. The discount factor, β, is set to 0.99, and the capital share, α, to 1/3. The labor disutility parameter, χ, is set such that steady state hours per worker equal 1. We set the steady state value of technology, A, equal to 1. Parameters which are specific to ESAM are set as follows. The rate of business destruction, δ, equals 0.025 to match the U.S. empirical level of 10 percent business destruction a year reported by Bilbiie et al. (2012). Similarly, we set the depreciation rate of physical capital, δ^k, equal to 0.025, to match an average depreciation rate of 10% per year. The constant part of the entry cost, ψ_0, is set to 1, as in Bilbiie et al. (2012).

Next, we turn to parameters that are specific to the search and matching framework. The total separation rate, $1-(1-\delta)\varrho$, is set to 0.1, as suggested by the estimates provided by Hall (2005) and Davis and Haltiwanger (1990). We set the steady state job market tightness to target an average job finding rate, z, equal to 0.7 as in Blanchard and Galí (2010). This amounts to a monthly rate of 0.3, consistent with U.S. evidence.

The vacancy filling rate, q, equals 0.9 as in Andolfatto (1996) and Den Haan et al. (2000). The cost of posting a vacancy κ is implied endogenously. The steady state rate of unemployment reads as $u = \frac{(1-(1-\delta)\varrho)}{(1-(1-\delta)\varrho)+q\theta}$, which is increasing in both the firm-level job separation rate, ϱ, and in the rate of business destruction, δ. As expected, the unemployment rate is decreasing in the job filling probability, q. The endogenous steady state rate of unemployment is higher than the one observed in the U.S. However, this is justified by interpreting the unmatched workers in the model as being both unemployed and partly out of the labor force. As argued by Trigari (2009), this interpretation is consistent with the abstraction in the model from labor force participation choices.[25] The steady state ratio between jobs created by new firms (JC^{new}) and total job creation (JC) is given by

$$\frac{JC^{new}}{JC} = \frac{(1-\delta)\,N^e v^{new} q}{v^{tot} q} = \frac{\delta}{\theta q}\frac{(1-u)}{u} = 0.25$$

The calibration implies that job creation by new producers accounts for about 25 percent of total (gross) job creation, close to the quarterly U.S. average of 20 percent reported by Jaimovich and Floetotto (2008). Finally, the ratio between workers employed by the first period incumbent firms (L^{new}) and total employment (L) is given by

$$\frac{L^{new}}{L} = \frac{(1-\delta)\,N^e \frac{L}{N}}{L} = \delta\ .$$

In our baseline calibration $\delta = 0.025$. As a result, steady state employment at new firms is 2.5% of total employment, slightly lower than the 3 percent reported by Haltiwanger et al. (2013) as the average value for the U.S. between 1976 and 2005. Thus, in ESAM new entrants create, on average, a relevant fraction of new jobs, while accounting just for a small share of overall employment, in line with U.S. data.

[25] Krause and Lubik (2007) calibrate their model to deliver an unemployment rate of 12 percent on the basis of this motivation. Many studies in the search and matching literature feature much higher unemployment rates. For example, Andolfatto (1996)'s model features a steady state unemployment rate of 58 per cent, while Trigari (2009) is characterized by an unemployment rate equal to 25 percent.

6 Results

In what follows we provide the parameters of ESAM, SAM, and WSAM estimated using the technique described in Section 5.1. We compare across models the IRFs to the shocks that we identified in the VAR analysis. Lastly, we use the log marginal likelihood to evaluate their relative statistical fit.

6.1 Parameters estimation

In this section, we compare the estimated parameters across the models. Table 3 reports means and standard deviations of the implied posterior mode distributions for the structural parameters in ESAM, SAM, and WSAM. The mean values and the standard deviations are here calculated over the 500 posterior parameters modes obtained from the minimum distance estimation. Columns (1) and (2) of Table 3 refer to ESAM and SAM, respectively, while column (3) refers to WSAM. For the latter, we also estimated the degree of real wage rigidity, measured by the parameter ϕ_w.

Both ESAM and SAM require a high value of the replacement ratio, the parameter rr, to match the empirical IRFs. One relevant difference between the two models is the value assumed by the mean of the posterior modes of the bargaining power of workers, η. Specifically, to be consistent with the empirical evidence, SAM needs a low bargaining power of workers. On the contrary, ESAM calls for a value of the bargaining power in line with that used by the bulk of the literature.

As well known, a low relative bargaining power of workers together with a high replacement ratio, dampens the response of the real wage to shocks. The values of estimated parameters in SAM are thus trying to introduce a form of wage moderation in response to shocks.

Once SAM is augmented with real wage rigidities, i.e. when we consider WSAM, a low bargaining power of workers is no longer required to replicate the empirical evidence. Indeed, the value of η estimated in WSAM comes close to that in ESAM.

We interpret these results as suggesting that the extensive margin of investment delivers an endogenous form of wage moderation that is absent in the SAM model, but characterizes models with wage inertia such as WSAM. We further investigate this point when discussing the IRFs in the next section.

Parameter	(1) *ESAM*		(2) *SAM*		(3) *WSAM*	
	Mean	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
ρ_a	**0.777**	0.053	**0.767**	0.063	**0.763**	0.059
ρ_ε	**0.792**	0.086	**0.810**	0.088	**0.800**	0.084
ρ_η	**0.845**	0.069	**0.768**	0.098	**0.804**	0.081
σ_a	**0.003**	0.001	**0.002**	0.001	**0.002**	0.001
σ_ε	**0.009**	0.005	**0.009**	0.006	**0.009**	0.006
σ_η	**0.021**	0.012	**0.040**	0.028	**0.032**	0.018
φ	**2.100**	0.288	**2.017**	0.381	**2.080**	0.358
ϑ	**0.625**	0.066	**0.650**	0.079	**0.644**	0.075
η	**0.586**	0.134	**0.436**	0.166	**0.474**	0.155
γ	**0.457**	0.125	**0.468**	0.124	**0.466**	0.125
rr	**0.858**	0.090	**0.818**	0.100	**0.833**	0.098
ε	**4.457**	0.635	**4.580**	0.816	**4.557**	0.779
ϕ_I	**3.962**	0.408	**3.654**	0.547	**3.732**	0.516
ς	**2.073**	0.170	-	-	-	-
γ_w	-	-	-	-	**0.640**	0.091

Table 3: Posterior modes for DSGE structural parameters: ESAM, SAM, WSAM.

6.2 IRFs analysis

This section we trace out DSGE-IRFs to shocks to aggregate productivity, the price markup, and to the relative bargaining power of workers. To avoid excessive cluttering of the graphs, we initially compare ESAM to SAM, and then ESAM to WSAM. All the graphs display the 90% (light grey) and 68% (dark grey) probability credible intervals of the VAR-IRFs to the three shocks.

6.2.1 ESAM versus SAM

Figures 1 and 2 compare the IRFs of the macroeconomic variables generated by SAM and ESAM to the three shocks. Red solid lines embrace the 90% probability density intervals of the IRFs produced by ESAM. Dashed blue lines refer to SAM. The horizontal axis measures time in quarters, while the vertical axis reports responses in percentage deviations from the steady state.

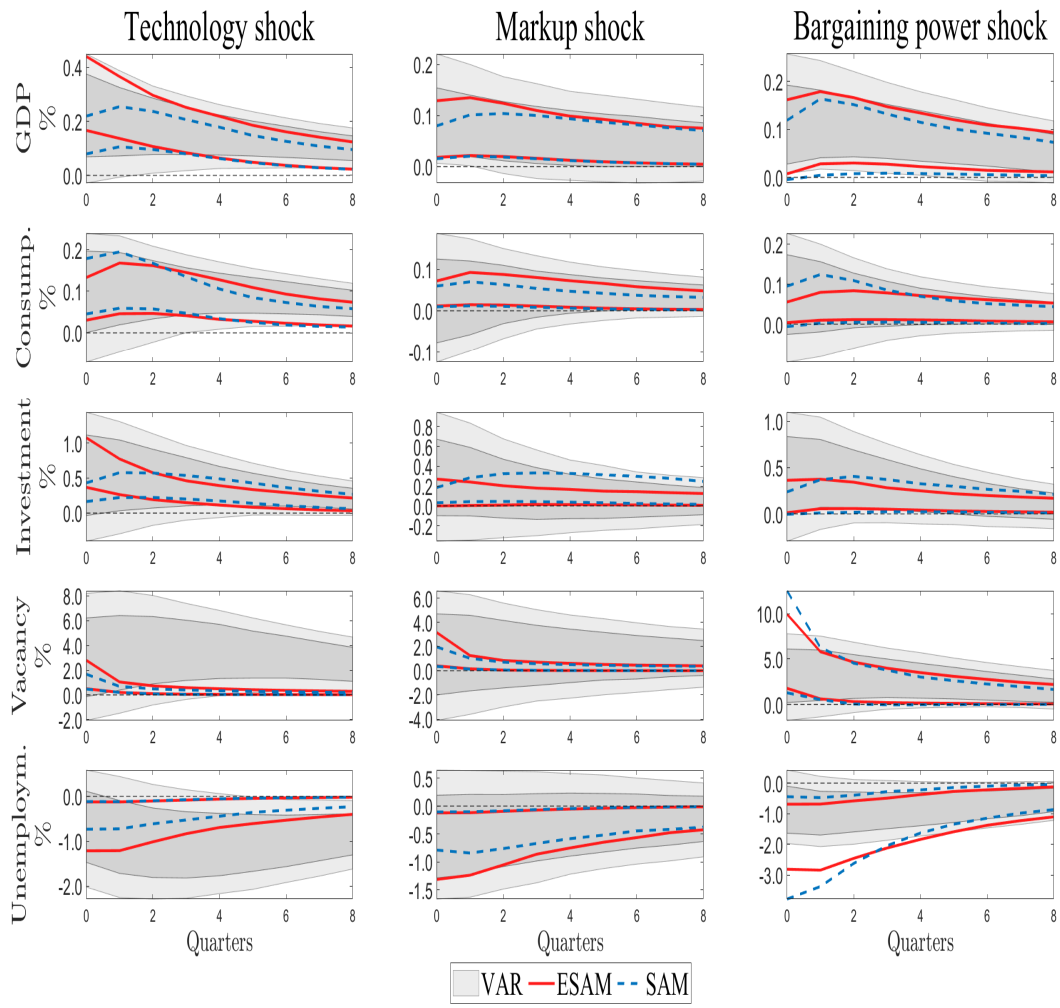

Figure 3: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, SAM in blue-dashed lines.

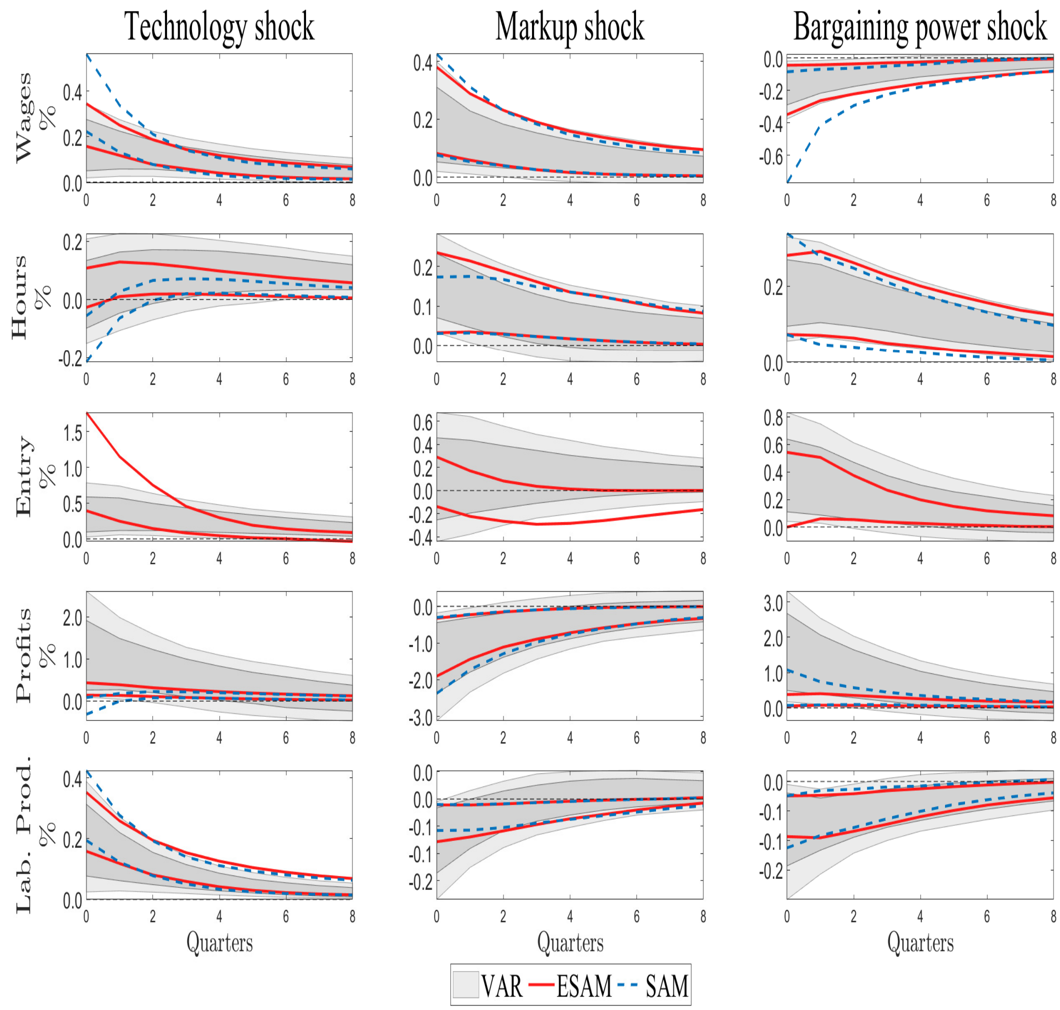

Figure 4: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, SAM in blue-dashed lines.

Figures 3 and 4 help describing the transmission of shocks in SAM and ESAM. The technology shock is the one that entails the most relevant differences between the two models. The shock leads to a temporarily higher wage. Households, desire to work more today to take advantage of the higher salary.

In SAM, the process of intertemporal substitution of labor does not prevent a sharp increase in the real wage, as displayed in Figure 4. Indeed, a large share of the IRFs for the real wage overreacts and exceeds the 90% percentile of credible intervals of the VAR-IRFs. In contrast, the IRFs of the real wage in ESAM overlap with the VAR-IRFs. In SAM, the increase in real wage also dampens the demand of labor by firms and impairs their profitability. As a result, total hours of work and profits are more likely to respond negatively to the shock. This stands in contrast with ESAM-IRFs and VAR-IRFs, which identify a positive response of both variables as the most likely outcome.

In ESAM, the increase in technology makes investment in new firms more attractive to households. To obtain resources to invest in new firms, households substitute labor intertemporally to a larger extent with respect to what they do in SAM. As a result, we observe a milder response of the real wage, in line with the VAR evidence, that leads to three empirically desirable implications. The first one is an increase in the response of hours worked. The second one is a positive impact response of profits. The last one is an increase in firm entry.

ESAM displays an amplified, with respect to SAM, response of GDP and unemployment to technology shocks. This is so for two reasons. First, given the wage does not suffer the sharp response observed in SAM, incumbent firms can expand to a larger extent, second the entry of new firms further contributes to job creation.

One potential concern with the results we just discussed is that the response of entry in ESAM overreacts to a technological shock compared to the VAR-based IRFs. To verify that this is not the source of the success of ESAM, we constrained the response of entry in ESAM to fall within the 90th percentile range of the VAR model and traced the corresponding responses of other variables. Figure 8 in the Appendix shows that this adjustment does not affect any of the previously discussed impulse response functions. In particular, the responses of hours worked and profits remain procyclical following the shock.

The performance of ESAM in response to other shocks is similar to that of SAM. However, SAM implies an overreaction of the real wage, vacancies, and unemployment to a bargaining power shock, while ESAM-IRFs for the same variables are within the 90% percentile of credible intervals of the VAR.

To verify that the endogenous wage moderation mechanism we just described is empirically relevant, in the next section we compare ESAM to WSAM, the version of SAM with exogenous wage rigidity.

6.2.2 ESAM versus WSAM

Figures 5 and 6 compare the IRFs of the main macroeconomic variables generated by ESAM and WSAM to the three shocks. As earlier, red solid lines embrace the 90% percentile of credible intervals of the IRFs of the ESAM model. Dashed green lines have the same meaning, but refer to the WSAM model.

In response to a technology shock, WSAM displays a more inertial response of the real wage with respect to ESAM. This is not surprising as wage inertia is exogenously imposed in WSAM. However, in WSAM hours of work decrease on impact under all relevant parameter configurations. In ESAM, instead, the impact response of aggregate hours is positive in a large area of the parameter space. This is in line with the VAR evidence that assigns a large probability to a positive response of hours. The reason is that the interaction between the asset market and the labor market featured in ESAM is absent in WSAM. In other words, the intertemporal substitution in labor is stronger in ESAM than in WSAM. Additionally, in the following paragraph, we argue that WSAM struggles to explain the dynamics of job creation in response to technology shocks.

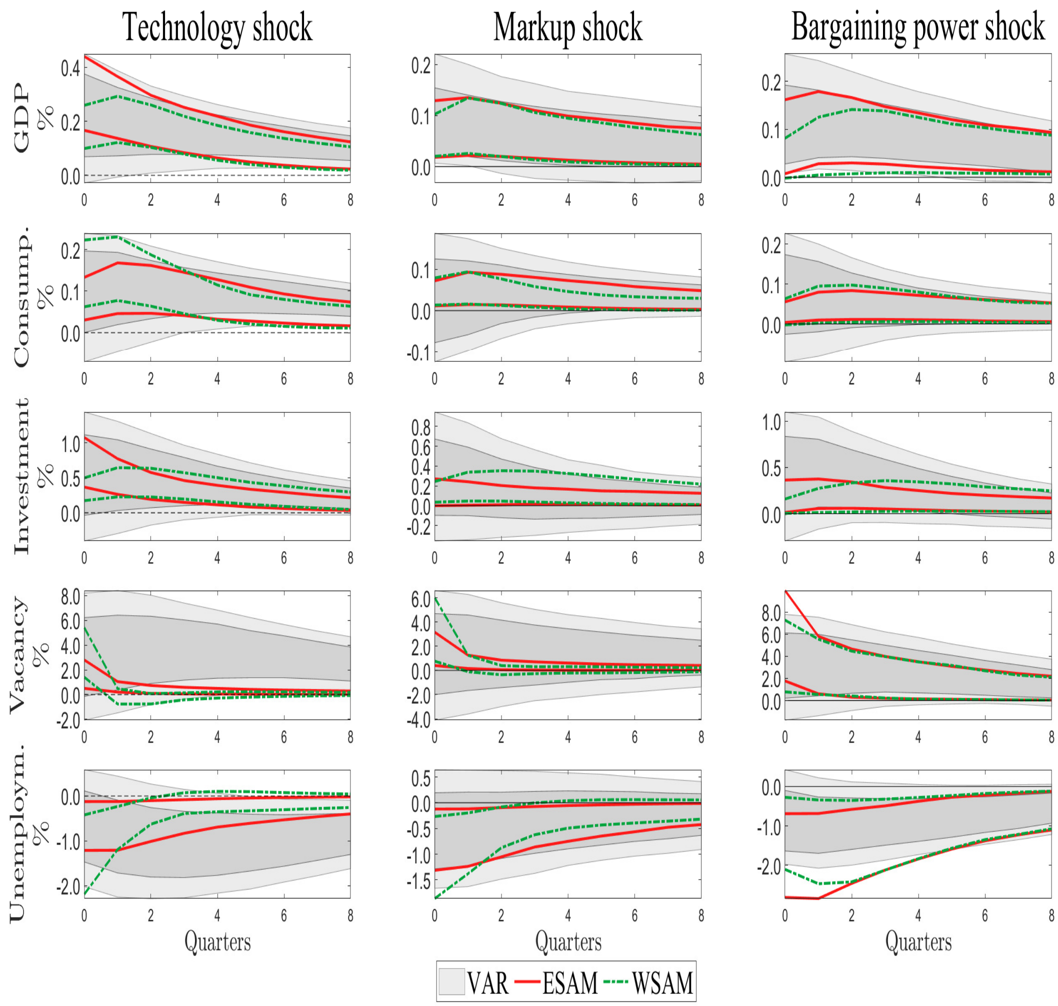

Figure 5: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, WSAM in green-dashed-dotted lines.

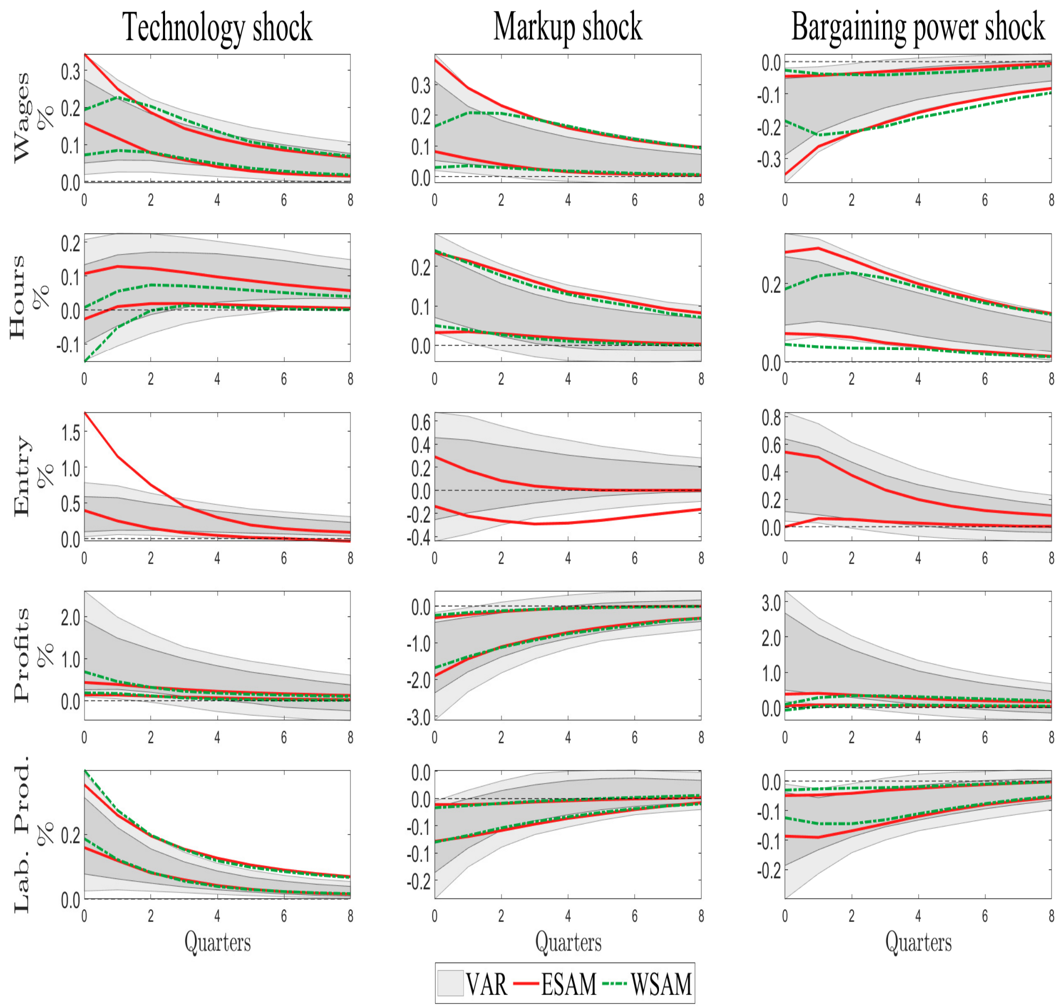

Figure 6: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, WSAM in green-dashed-dotted lines.

6.3 Job Creation

In this section, we analyze the dynamics of job creation in response to technology shocks comparing results from ESAM with empirical data and outputs from the other models we discussed. We focus on technology shocks since our analysis shows that entry frictions are specifically useful at reconciling the search and matching framework with the evidence concerning those shocks.

We augment the baseline BVAR model described in Section 3, with a quarterly job creation series. We draw on the Business Employment Dynamics (BED) database from the BLS, which provides quarterly job creation data from Q1 1993 to Q4 2016. As a result, our analysis in this section is limited to that timeframe. We apply the same specifications and variable transformations as in the benchmark BVAR, adding an additional restriction to identify technology shocks, namely that job creation increases on impact.[26] Figure 7 presents a comparison of the empirical impulse response functions for job creation, real wages, profits, and total hours against those generated by ESAM, SAM, and WSAM.[27] Values of parameters are set as described earlier, namely at the values estimated using the whole sample. Red solid lines embrace the 90% probability density intervals of the IRFs produced by ESAM. Dashed blue lines refer to SAM, and dashed-dotted lines refer to WSAM. We also display the 90% (light blue) and 68% (dark blue) probability credible intervals of the VAR-IRFs to the three shocks. The empirical dynamics of wages, hours worked, and profits align with those obtained using the full sample. Hence, the relative performance of models at explaining them is unchanged, with ESAM being preferred to the competitive alternatives, especially at explaining the response of total hours. In terms of job creation, the dynamics produced by SAM and ESAM are nearly identical and consistent with the empirical ones. In contrast, job creation in WSAM initially overshoots and then undershoots compared to its empirical counterpart. Thus, while real wage rigidity improves SAM's ability to explain the responses of wages and profits, it leads to a response of job creation that does not align with the data.

[26] This holds true for all the models we analyze, so this restriction does not give ESAM an advantage over the others.

[27] The empirical IRFs of other variables are reported in the online Appendix. They are consistent with those obtained using the baseline BVAR.

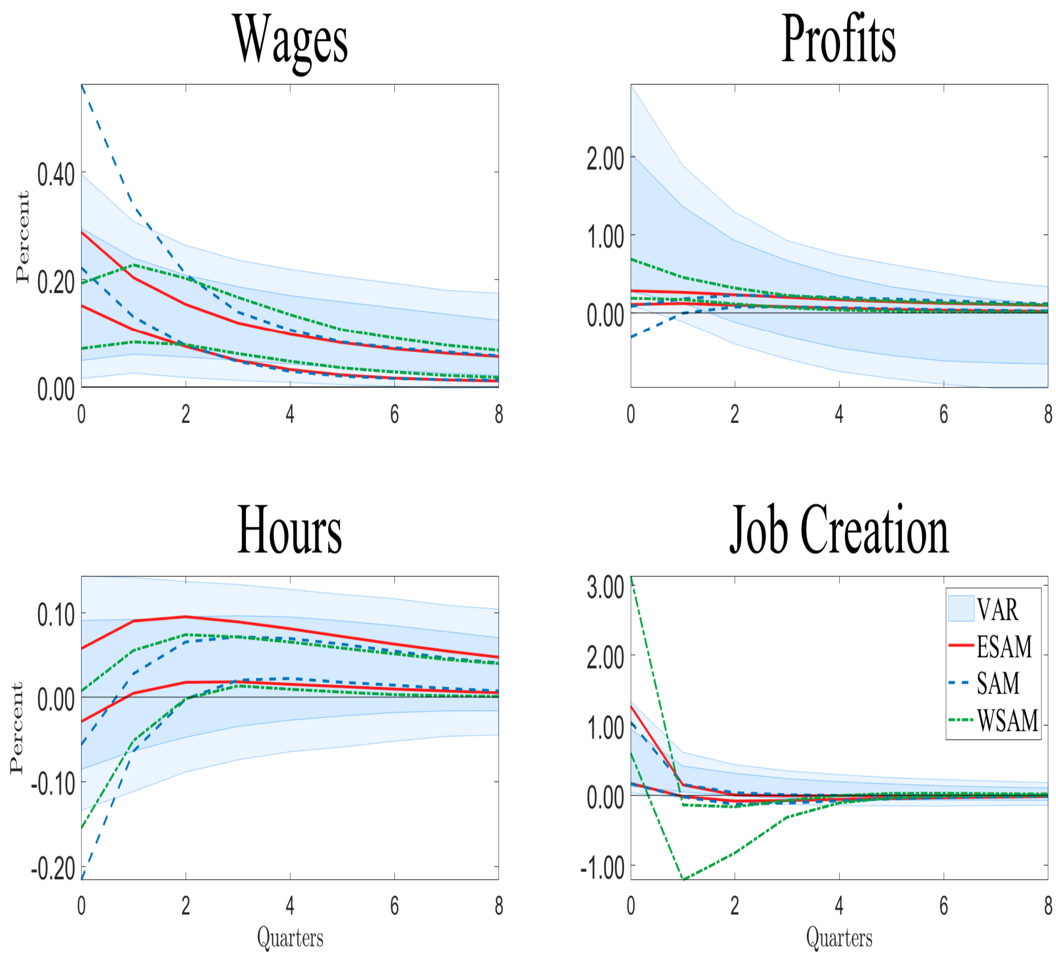

Figure 7: Dynamic responses in percent to the aggregate productivity shock in VAR embedded with job creation data (blue area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, SAM in blue-dashed lines, WSAM in green-dashed-dotted lines.

6.4 Statistical fit

As a final step, we compare the statistical fit of the models we estimated. To do so we refer to the whole sample. The metric adopted for the comparison is the log marginal likelihood. The latter is computed using a Laplace approximation around the posterior modes of the estimated parameters. Since the minimum distance estimation provides us with a set of vectors of posterior modes, one for any of the 1000 VAR-IRFs, we also obtain 1000 values of the marginal likelihood for each of the models we consider. At each estimation round, so taking a specific VAR-IRFs as a reference, we subtract from the log marginal likelihood delivered by ESAM that is obtained from the competing alternative. As in our estimation, the VAR-IRFs can be regarded as the data, this exercise amounts to comparing the ability of our models at generating the same dataset, i.e. the same VAR-IRF.[28] Columns (1) and (2) of Table 4 provide summary statistics concerning the comparison of the models through their marginal likelihoods. Taking the full distribution of marginal likelihoods across the 1000 estimation runs for each model, column (1) displays the mean value, while column (2) reports the standard deviation. Considering mean values, the marginal likelihood of ESAM is 28 log points higher than that of SAM and 13 points higher than that of WSAM. We also compare the ability across models at generating the same VAR-IRF, that is taking the same dataset. The fraction of runs in which ESAM delivers a higher value of the marginal likelihood with respect to the competing model given the same VAR-IRFs (% of wins for ESAM) is reported in Column (3) of the Table. ESAM displays a higher marginal likelihood than SAM and WSAM in 90% of the cases.

Model	**(1) Mean**	**(2) Std.**	**(3) % of wins for ESAM**
ESAM	298	83	-
SAM	270	91	92.77%
WSAM	285	80	92.37%

Table 4: Laplace approximation for marginal likelihood: ESAM, SAM, WSAM. Values in log-points.

7 Extension: Nominal Price Rigidities

In this Section, we enrich the models analyzed earlier with price rigidities. The price-setting mechanism follows Rotemberg (1982), where firms face a quadratic cost of adjusting nominal prices. We dub the ESAM model with price rigidities as New Keynesian (NK) ESAM, NK-ESAM in short. The NK version of the SAM model is defined as NK-SAM, while the version of the SAM model with nominal price rigidities and real wage inertia is denominated NK-WSAM.

[28] For this reason, we compare the marginal likelihood of the models relative to the same VAR-IRF, and not the marginal likelihoods relative to different VAR-IRFs.

When prices are sticky, the dynamics of the number of firms affects the definition of the price markup. In the interest of saving space, and to lighten the reading, we report the details of the derivations and IRFs to the three shocks we consider in the online Appendix.

Including the VAR-IRFs of inflation among the observables in the minimum distance estimation procedure improves the fit of all models, without altering their relative performance. As we did in the case of flexible prices, at each estimation round, so taking a specific VAR-IRFs as a reference, we subtract from the log marginal likelihood of NK-ESAM that obtained from the competing model. Column (5) of Table 5 reports the fraction of runs in which NK-ESAM delivers a higher value of the marginal likelihood with respect to the competing model (% of wins for NK-ESAM). The percentage of wins for NK-ESAM with respect to NK-SAM exceeds 97%, while it equals 95% in the case of NK-WSAM.

The mean value of the marginal likelihood of NK-ESAM is 49 log-points higher than that of NK-SAM, and 33 log-points higher than that displayed by NK-WSAM. Similar differences hold considering the median values displayed in Column (2).

For these reasons, we argue that the propagation mechanism resulting from the endogenous wage moderation characterizing ESAM extends to models featuring nominal price rigidities.

Model	**(1) Mean**	**(2) Std.**	**(3) % of wins for NK-ESAM**
NK-ESAM	397	93	-
NK-SAM	248	102	97.29%
NK-WSAM	364	101	94.96%

Table 5: Laplace approximation for marginal likelihood: NK-ESAM, NK-SAM, NK-WSAM. Values in log-points.

The online Appendix shows the Tables containing the estimated parameters of the NK-ESAM, NK-SAM and NK-WSAM, as well as the results of the respective IRFs matching. It shows that the inclusion of New Keynesian features further improves the performance of ESAM in replicating the dynamics of the main macroeconomic variables over the business cycles, particularly of labor market variables.

8 Conclusions

This paper formulates and estimates an equilibrium business cycle model that accounts for the joint response of firm entry, profits, unemployment, hours of work, and other U.S. aggregates to neutral technology shocks, markup shocks, and shocks to the bargaining power of workers. One key feature distinguishes our model from the standard search and matching model of the labor market: frictional firm entry that results in an extensive margin of investment. Investment in new productive units is financed by households on the stock market. We argue that the interaction between the asset market and the labor market leads to a form of wage inertia. The latter enables our model to explain the joint responses of profits, entry, and hours of work to technology shocks. The statistical fit of our model with firm dynamics at replicating the US business cycle is substantially higher than that of a baseline search and matching framework enriched with exogenous wage rigidities. Considering price rigidities does not alter our findings. Microeconomic data suggest a pervasive heterogeneity in terms of size and productivity among active firms. The interplay between firm dynamics and aggregate shocks determines the composition of active product lines and thus aggregate productivity. Identifying empirically the interaction between the composition of the pool of producers and the propagation of shocks to the labor market is a promising avenue for future research.

Appendix

The Standard Search and Matching Model: SAM

This section describes the SAM model with fixed variety that we take as the reference to evaluate the role of the extensive margin of investment for the cyclicality of labor market variables. This version of the model is well established in the literature. It can be regarded as a medium scale version of the search and matching model described, *inter alia*, by Trigari (2009).

The key differences with respect to the ESAM model are that there are no entry frictions and the number of varieties is fixed. For this reason, there are no product development costs. As a result, in equilibrium households will invest uniquely in physical capital. In this case, the aggregate resource constraint of the economy reduces to

$$C_t + I_t^k = w_t h_t L_t + r_t^k K_{t-1} + PRO_t, \tag{35}$$

and the dynamics of employment reads as

$$L_t = \varrho L_{t-1} + q_t v_t^{tot}.$$

Other equations are analogous to those in ESAM, and are reported in the online Appendix.

SAM with Real Wage Rigidities: WSAM

Starting with Hall (2005), the literature pointed out that in order for SAM models to account for the cyclical properties of unemployment and vacancies the real wage should not display sharp changes in response to shocks. This has led several authors to augments the SAM framework with a wage norm that dampens fluctuations in the real wage. For this reason we augment the SAM model with real wage rigidities. Following Shimer (2005) and Hall (2005), we model real wage rigidity in the form of a backward-looking social norm:

$$w_t = w_{t-1}^{\phi_w} \left(w_t^*\right)^{1-\phi_w}, \tag{36}$$

where ϕ_w is a parameter reflecting the degree of real wage rigidity and w_t^* is the wage obtained under the Nash bargaining between firms and workers, namely that in equation 26. Notice that $\phi_w = 1$ implies a fixed real wage, while $\phi_w = 0$ corresponds to the case of Nash bargaining analyzed above. Shimer (2005), Hall (2005), and Blanchard and Galí (2010) studied the implications of equations similar to (36) for fluctuations in wages, employment, and unemployment over the business cycle.[29] We define the version of the SAM model augmented with exogenous wage rigidity as WSAM.

Constrained entry in ESAM in response to technology shocks

In this Section we display key IRFs when the response to technology shocks of entry in ESAM is constrained to fall within the 90th percentile range of the VAR model. Solid lines in Figure 8 refer to ESAM when the response of entry is unconstrained, i.e. our baseline version, while dashed lines to the case where entry is constrained. As discussed in the text, the procyclicality of hours worked and profits to the shock holds also in the constrained model.

[29] Gertler and Trigari (2009) introduce staggered multiperiod wage contracts in the SAM model, where a firm has a fixed probability to renegotiate the wage in each period. Our simple equation (36) though admittedly *ad-hoc*, suffices for our purposes. Our aim is indeed not that of estimating the frequency of wage adjustment, but that of understanding how ESAM performs against a model which features an explicit slow wage adjustment in response to shocks.

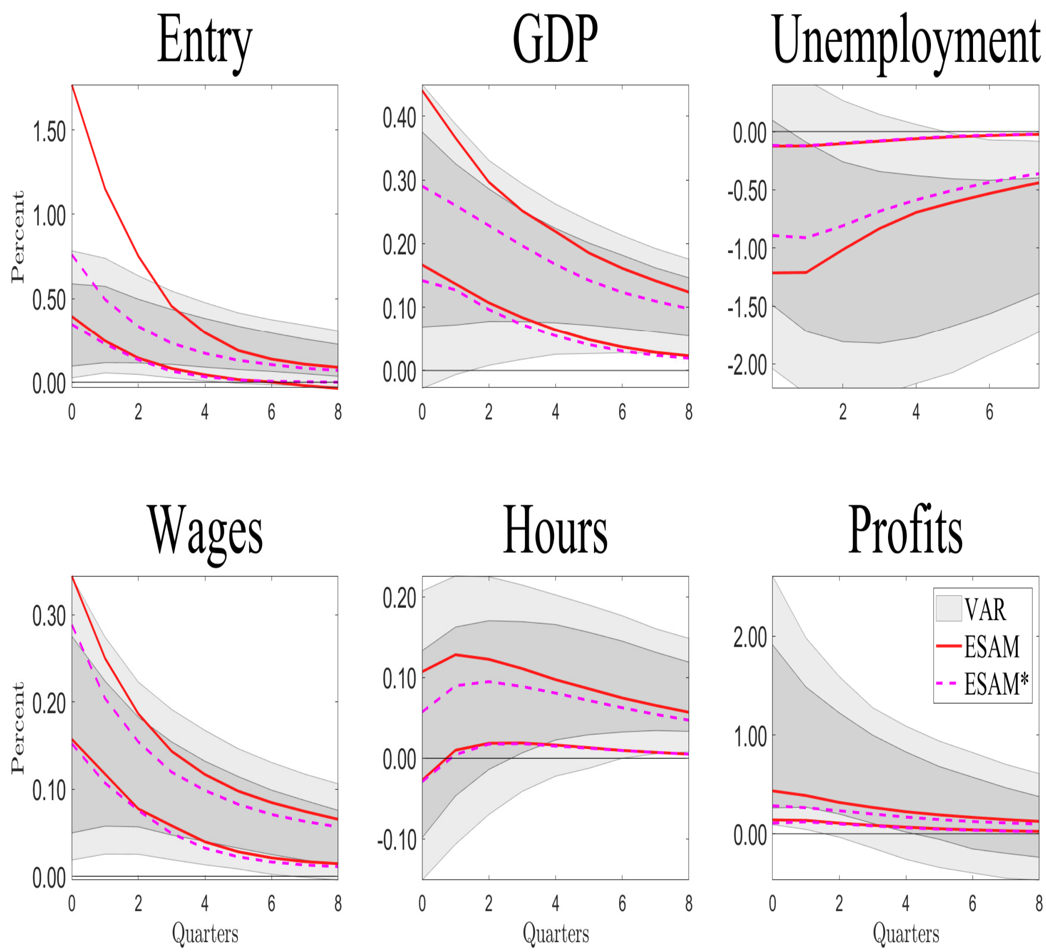

Figure 8: Dynamic responses in percent to structural shocks in VAR (gray area: 68% and 90% percentile coverage) and in DSGE models (90% percentile coverage). ESAM in red-solid lines, *restricted* ESAM in magenta-dashed lines.

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