No Noise in Job Creation

Philip Schnattinger *

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Abstract

The question on whether firms separate temporary from permanent labour productivity shocks and adjust their hiring policies accordingly is important as it is crucial for interpreting labour market data. It is becoming more prevalent as more data on current firm vacancies and future firm hiring expectations is becoming increasingly available. This paper implements a framework to estimate the extent to which job creation is influenced by non-fundamental noise impacting agents' ability to separate temporary from permanent changes in the productivity of a job match. For this purpose, it sets up a small scale DSGE equilibrium unemployment growth model, where current and future labour productivity expectations drive hiring activity and job creation. Agents receive a noisy signal, which may allow them to separate temporary from permanent labour productivity changes. A higher noise component in predicting future productivity will lead to more similar job creation responses of agents following either kind of fundamental shock as agents cannot be sure whether labour productivity has permanently changed. Noise may cause the signal, and noise shocks will look in the data like spontaneous increases in labour demand, which cannot be justified by the productivity of employed workers. The paper estimates the extent to which aggregate job creation is driven by non-fundamental noise about the productivity process, and to which extent agents can separate temporary from permanent labour productivity shocks. For robustness, a structural VAR model using an alternative identification of noise based on an observed signal is also estimated. Both methods find that it is unlikely that agents' information sets are significantly impacted by noise. Hence noise plays a significant role in aggregate hiring and job creation in the United States labour market, and agents are able to separate temporary from permanent labour productivity changes well. This means that series measuring labour market hiring decisions and future hiring intentions are reliable predictors of rationally expected future labour productivity changes and that aggregate labour market decision-making is unlikely to be impacted by non-fundamental noise.

Keywords: *Labour productivity, Information frictions, News and Noise, Temporary and permanent shocks, Equilibrium unemployment growth model, Search and Matching, Labour Markets, Business Cycles*
JEL Classification: *E2; E24; E32; E37.*

*Bank of England. Any views exsressed here are solely those of the author and do not represent those of the Bank of England or any of its committees. Contact: philip.schnattinger@bankofengland.co.uk.
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Contents

1 Introduction

Do job creation decisions reflect that some labour productivity shocks are temporary and some are of a permanent nature or do firms struggle to separate these shocks? This is an important question for policymakers judging the current state of the labour market and its future trajectory as new data on current firm vacancies and future firm hiring expectations is becoming increasingly available. This paper uses a small scale dynamic stochastic general equilibrium model to structurally estimate the extent to which agents are able to separate shocks increasing labour productivity permanently, from temporary shocks by using a small scale DSGE model with an agent information problem and search frictions in the labour market.

This paper adapts the methods for estimating news and noise around productivity in consumption developed in (Blanchard, L'Huillier, and Lorenzoni, 2013) to labour productivity in an equilibrium employment growth model in the spirit of (Pissarides, 2000). First, the paper shows that the neutrality result proven in (Shimer, 2010) that productivity shocks neither affect the labour wedge not the unemployment rate in the standard equilibrium employment growth model also applies to expectation shocks. To overcome this neutrality result and capture the impact of labour productivity on unemployment in congruence with the data a simple new method tractable proposed and calibrated to the data, which summarises the impact of previous more extensive theoretical work. We then proceed with the estimation of the model, which finds that agents face no significant noise in separating temporary and permanent labour productivity shocks, suggesting agent current hiring activity, as well as expectations of future hiring activity are based on a non-noisy information set and thus provide reliable information to policymakers on the future labour productivity path.

For robustness, the paper also estimates the noise component in job creation by using an alternative identification method for noise in a structural VAR model developed in (Forni, Gambetti, Lippi, and Sala, 2017). To the author's knowledge, this paper is the first to offer an estimation on the ability of firms to separate permanent and temporary productivity shocks and of the extent to which fundamental and non-fundamental expectations shifts drive job creation.

A consequence of costly job creation is that the decision of a firm on whether to employ a worker is influenced by a substantial forward-looking component. When deciding on how much to spend on hiring new workers, the firm's management will look to the current and the expected future value that the new hire would bring to the firm. These added values will usually have to outweigh the costs that come with hiring, training, paying, and integrating the new worker into the production process. Similarly, a prospective worker deciding whether to take a job will weigh the benefits of the job, namely the wage, and the future career and income prospects, against the opportunity cost of not being able to devote her time to other productive activities. The forward-looking component will mean that expectation shifts may drive job creation. By embedding this noisy information structure with regard to future labour productivity in an equilibrium unemployment model with search frictions the information problem determining the forward-looking job creation decision can be estimated.

While the literature has found that a substantial part of the movements in aggregate consumption is driven by non-fundamental noise rather than fundamental news about productivity, this paper finds that noise plays no significant role in job creation decisions. This means forward-looking agents face substantial information frictions when making consumption or investment choices based on expectations about the future, but similar information frictions play no significant role in job creation decisions. Thus variables capturing hiring behaviour are reliable indicators of agents' expectations about fundamental labour productivity, and vice versa expectations are strong predictors of expected hiring activity. Concretely, the DSGE model finds that while reasonable model calibrations would allow for noise to make up to 24 % of the forecast error variance of employment to expectation shocks in the first quarter, maximum likelihood estimation shows that noise is likely to make up less than 0.1%. The structural VAR model confirms the result and shows that noise only makes up a small part of the forecast error variance of employment and the job-finding rate.

Optimal inter-temporal hiring decisions are at the heart of the Mortensen-Pissarides search and matching model ((Mortensen and Pissarides, 1994), (Pissarides, 2000)), where they are captured with the job creation condition. Matching frictions thereby provide another channel in business cycles models, besides the conventional consumption Euler equations, through which the present equilibrium may be affected by shifts in the expectations over future economic fundamentals, commonly referred to as news shocks. Empirically it has been shown that accounting for this channel by combining matching frictions, or other adjustment costs to labour input, with news shocks in a business cycle model, greatly improves the match of the model with the data ((Den Haan and Kaltenbrunner, 2009), (Jaimovich and Rebelo, 2009), and (Zanetti and Theodoridis, 2016)). A reason for this is that theoretical real business cycle models with search and matching frictions are able to produce the Pigou cycles that seem to be present in the data ((Beaudry and Portier, 2006), (Den Haan and Kaltenbrunner, 2009), (Krusell and McKay, 2010); see section 2 for a definition of a "Pigou" cycle). Thus a good part of aggregate job creation seems to occur in response to shifts in anticipations about future productivity, and this fact is reflected in the visible interest of investors and policymakers in new releases of the US employment report, and especially the changes in the number of non-farm workers on payroll.

Noise shocks could be considered wrong news, which lead agents to erroneously adjust their expectations over future productivity. As both aggregate consumption and aggregate job creation depend to an extent on the anticipated state of future economic fundamentals, recent findings on consumption being driven by noise raise the question of whether some fluctuations in the labour market can also be attributed to noise rather than news. Such noise shocks would look in the data like spontaneous changes in labour demand and hiring activity, which cannot be justified by current or future productivity changes of the employed worker. A large noise component in the information available to agents would further mean that expectations about future productivity are less precise, leading labour market participants to adjust their behaviour more gradually in response to labour productivity changes. The empirical question answered by this paper is how precise are agents' aggregate expectations about the value that employment relationships will provide, and thereby how much information about future fundamentals is contained in current labour market data.

To answer this question, a DSGE model with search frictions is developed in which variations in job creation, and thereby employment and the number of open vacancies, depend on news or noise about the future. This is achieved by combining a framework in which agents receive noisy information over future productivity growth as developed in (Lorenzoni, 2009) and (Lorenzoni, 2011), and (Blanchard et al., 2013) with a search and matching model of the labour market.

Firms and workers are modelled as facing a noisy information problem in separating temporary and permanent productivity changes. Noise determines the extent to which agents can separate temporary from permanent labour productivity shocks, and adjust their hiring behaviour accordingly. While a high noise environment will be reflected in firms and workers being unable to separate the shocks and hence reacting similarly to either in the short run, a low noise environment will mean short bursts of hiring and a period of labour reduction in response to temporary productivity improvements and a prolonged period of job creation and employment above steady state in response to a permanent productivity improvement. Noise shocks finally may cause non-fundamental shifts in labour demand.

The intuition of this model is the following. Agents receive a noisy signal providing them with information about labour productivity the permanent component in the labour productivity process. The signal provides firms with information about the expected relative value of opening a vacancy. Similarly, workers receive information about the value of an employment relationship, which will inform their wage negotiation. Agents know through long-term observation both how volatile the labour productivity processes are and how noisy the signal is. These distributional parameters will influence the extent to which rational agents trust the information about the future received through the signal, and thus the speed and strength with which the agents will react to the information obtained via the signal. Concretely, in this case, the amount of additional vacancies firms open will depend on the parameters of the productivity and noise innovations. Since we have information about both actual labour productivity and labour market outcomes, as well as the optimal response chosen by firms and workers given their productivity expectations, we can gain information about the nature of the signal driving expectations without the need to observe this signal. If the behaviour of agents anticipates future movements in the productivity process accurately and speedily then the signal is not very noisy, while if the behaviour of agents leads to fluctuations in labour market outcomes without movements in the productivity series and vice versa, then noise would be identified as being an important driver of the labour market on the aggregate level.

The setup of the paper allows for both estimating noise regarding shifts in the long-term fundamental surplus of matches in the labour market, as well as temporary increases in the match surplus. Furthermore, different standard calibrations of an equilibrium unemployment model following (Shimer, 2005) and (Hagedorn and Manovskii, 2008) are employed. The simulated model shows then that there exist calibrations consistent with US employment moments, where a substantial part of the forecast error variance in the employment rate one quarter ahead is caused by noise, and agents are slow to separate permanent form temprorary labour productivity shocks. However, bringing the model to the data and estimating the parameters of the news and noise process by maximizing their likelihood, yields the result that the volatility of the noise shock is very small. The results of this estimation suggest that when agents receive information about the future productivity of a job match, then this information is very precise and noise plays only a small if any, role in employment fluctuations.

An analysis employing the techniques suggested in (Forni et al., 2017) confirms the result of the DSGE model. (Forni et al., 2017) suggest to identify structural noise and productivity shocks in a VAR model with the help of a variable that acts as a proxy for the actual signal on future productivity observed by the agents. The idea of the structural VAR model in this paper is to take the insights about the behaviour of the labour market obtained in the DSGE model and set up auto-regressive equations which capture the expected reaction of the job-finding rate and the employment rate with respect to news and noise shocks. By introducing additionally a variable to measure expectations and thereby act as a proxy for the signal, the model assumptions are used to identify news and noise shocks. The results of the structural VAR model show that a majority of fluctuations in the labour market is found to be caused by correctly anticipated or surprise fluctuations in productivity. Of the anticipated fluctuations, on average more than 90 % of the forecast error variance in the job-finding rate and in the employment rate in the first four quarters are found to be caused by news, while less than 10% are due to noise confirming the results of the DSGE model.

This paper is structured in six parts. The first part situates the paper within the literature by providing an overview of the recent advancements in the research on news and noise shocks. In the second part, a DSGE model with search frictions for estimating the news and noise components in the labour market is presented. In the third part, the data used is presented and the DSGE model is calibrated, simulated and estimated. The fourth part compares the results of the maximum likelihood estimation in the third part to the results of a structural VAR following the identification of noise by means of dynamic rotations of the reduced form residuals proposed in (Forni et al., 2017). Section five discusses the interpretation of the result. Section six concludes and relates the findings for the labour market to the findings for aggregate consumption.

2 Relation to the literature

The paper follows an extensive research programme studying how shocks to expected future productivity drive present agent behaviour and market outcomes. It focuses on the labour market as this market has been shown to be both enabler and driver of these outcomes and picks up the results of the news literature that search and matching frictions, or other labour market frictions that create labour adjustment costs, create Pigou cycles in response to news shocks, which match the data well. Due to the empirical results produced by this literature and described in the next paragraphs, it is taken as given throughout this paper that hiring in labour market depends to a large extent on anticipations about the future productivity of the hired workers.

The renewed interest of macro-economists in news shocks can be traced back to Beaudry and Portier's seminal 2004 and 2006 papers. (Beaudry and Portier, 2004) proposed a model, which aimed to explain boom and recession cycles as the result of agents' difficulty in anticipating future needs for capital in production. This required diverging from the standard RBC model as *"such models are incapable of generating Pigou cycles, that is they are incapable of generating equilibrium paths in which: (i) a forecast of future technological improvement first leads to a boom defined as an increase in aggregate output, employment, investment and consumption, and (ii) the realization that a forecast is too optimistic leads to a recession defined as a fall in all the same aggregate quantities."*((Beaudry and Portier, 2004), p. 1185). (Beaudry and Portier, 2006) shows that the data supports the existence of Pigou cycles, and that models capable of producing these cycles are necessary for modelling the effect of anticipation changes correctly. The search and matching model employed in this paper can produce such Pigou cycles.

This empirical finding led to the search of theoretical models that could actually produce Pigou cycles in response to news shocks. To produce such cycles in an RBC model, (Jaimovich and Rebelo, 2009) suggest changing the utility function of the representative agents, including variable capital utilization, as well as adjustment costs for factor inputs. It finds that including labour adjustment costs in the model helps in generating aggregate co-movement in response to news shocks for a much wider range of parameters. The reason for this is that labour adjustment costs provide an increased incentive for smoothing labour input and thereby lead to a strong increase in labour supply in response to a news shock.

This effect of building up labour input in response to an expected productivity increase is also present in a model that takes a flow perspective of the labour market. This is used in (Den Haan and Kaltenbrunner, 2009), which adapts a search and matching model of the labour market such that it produces Pigou cycles. The model consists of endogenous entry in the job market, a labour market with matching frictions, and an otherwise frictionless capital market. Both the cost of finding a worker for a job as well as the capital for the job itself are interpreted as investment. As the flow constraints of the model are such that both current employment and current capital are predetermined state variables, the model cannot produce a Pigou cycle behaviour in the first period of a news shock as total output remains constant. In order to get a sufficiently volatile response of employment in the face of news shocks, (Den Haan and Kaltenbrunner, 2009) furthermore introduce sticky wages and set the bargaining power of the worker higher than the level of Pareto-optimality. With this set-up, they manage to produce Pigou cycles, which match the empirical moments closely. (Krusell and McKay, 2010) point out that even a simpler Mortensen-Pissarides search and matching model produces Pigou cycles, if the focus is on the periods following a news shock and the cost of finding a worker is interpreted as investment. (Zanetti and Theodoridis, 2016) show that an RBC model enriched with conventional search and matching frictions, variable capital utilization, and investment adjustment costs does well in matching the data. An estimation of the model on aggregate and labour market data shows that news shocks to labour market variables such as the job destruction rate and the matching productivity actually decrease the fit of the model with the data, while news shocks to aggregate productivity increase the fit with the data. Furthermore, the estimation shows that most short-run fluctuations are due to surprise shocks, while long-run fluctuations are caused by news shocks.

The papers above usually assume that the productivity series is subject to two types of shocks. These are news shocks and surprise shocks. News shocks determine the future productivity path, while surprise shocks in the current period may lead to sudden corrections. This assumption has the advantage of simplicity, however, it comes with some empirical and normative drawbacks. There may exist, for instance, a third type of shock that is not identified by the econometrician in this setup. This could be a shock, which shifts expectations, but contains no actual news on the future values of productivity. These kinds of shocks are interpreted by some authors as Keynesian animal spirits, following (Keynes, 1936). A more sober interpretation may be to view these shocks as noise in the news that agents receive over future productivity.

Not accounting for the noise shocks has the empirical drawback that it may lead to an overestimation of the importance of surprise shocks, or news shocks depending on the setup and identifiers used for estimating the shocks. For example, if every expectation shift is seen as a news shock, then the only possibility to correct for erroneous news is a surprise shock. Similarly, if noise leads to similar impulse responses as news in the short run, then a two shock model in a noisy environment will overestimate the importance of news in driving business cycles. On the normative side the following dichotomy arises. On the one hand, if agents receive news and are afterwards subject to surprise shocks, which correct for the news received at an earlier time, then the choices made by the agents at all times must be viewed as optimal. On the other hand, if agents are making choices based on false news, then an all-knowing social planner could improve on the choices made by rational agents. Whether noise is an important source of fluctuations has thus become an important question in the recent literature on news.

(Lorenzoni, 2009) and (Lorenzoni, 2011) develop a setup for the productivity process that can be used for estimating the importance of noise shocks in business cycle fluctuations. The level of productivity is split up in a non-stationary permanent part and a stationary temporary part. Agents receive a noisy signal over the size of the permanent part and form expectations about future productivity growth based on this signal. These assumptions about the productivity process are also made in (Blanchard et al., 2013) and in the model in this paper (see section 3.1). (Blanchard et al., 2013) show that an econometrician who does not have information about the actual signal will be unable to recover this signal, and therefore also the basis for the agents' decision-making, with a structural vector autoregression. However, with a method of matching moments it will be possible to estimate the parameters of the assumed productivity and noise processes. Even more, with a maximum likelihood estimation and employment of the Kalman smoother, it is possible to estimate the parameters of the process and recover to some extent the shocks. Applying this method first on a simple model of productivity and consumption, and then in a DSGE model, the authors estimate that the volatility of noise and of temporary productivity shocks to be similar in size, which speaks for a significant role of noise in business cycle fluctuations.

Responding to the finding of (Blanchard et al., 2013) regarding the identification of noise shocks to the agent's information set without the signal variable, (Forni et al., 2017) show that if one changes the assumptions on the noisy signal slightly, a structural VAR model will be able to recover the correct shocks from the agents' decision-making. If one assumes that agents receive a noisy signal, where after a finite number of periods the agents learn exactly what part of the signal has been noise and what part has been news, then imposing the logical restriction that the noise does not affect actual productivity is sufficient to identify and recover the correct shocks. Like (Barsky and Sims, 2012) their estimation approach requires the choice of the series that serves as the signal. Furthermore, noise can only be separated from news up to the point where agents are able to separate noise from news as well, thus not at the most recent data points. Using US potential output as the productivity series and expected business conditions within the next twelve months as a signal, the authors find that more than half of the fluctuations of GDP are driven by noise and news. Noise is an essential part of these fluctuations and accounts for approximately 30-40% of the forecast error variance in the short run. Thus the authors conclude that noisy expectations of future fundamentals should be considered a major source of business cycle fluctuations.

The literature has thus arrived at the conclusion that consumption over the business cycle is likely to be driven to a large extent by noise. This also means that a good part of investment is likely to be driven to some extent by noise, leaving a limited set of variables to policymakers to judge the state of the economy. This paper shows that by employing similar techniques, labour market variables are not found to be driven to the same extent by noise.

3 The model

3.1 Firm-worker match productivity

This first Section 3.1.1 describes the fundamental match productivity process, which will define the output of all firm-worker matches in the economy. The next Section 3.1.2 specifies the information set, while the last Section 3.1.3 describes the solutions to the information problem. The agent Kalman filter presented is the focus of the estimation determining the quality of the information content about future labour productivity growth held by agents.

3.1.1 Productivity fundamentals

The model takes the labour productivity process formulated in (Blanchard et al., 2013) and applies it to a labour market with equilibrium unemployment. The observed individual match productivity process a in equation (1), is taken to be the flow product of a match and consist of an unobserved permanent component x and an unobserved temporary component z.

$$a_t = x_t + z_t \tag{1}$$

The difference between the permanent component and the temporary component are assumed to be stationary processes. The process x can be viewed as capturing permanent changes in production technology, while z captures short-term productivity deviations. e_t and η_t are independently, identically, and normally distributed exogenous shocks with mean 0 and constant and known variances σ^2_ϵ and σ^2_η.

$$\Delta x_t = \rho^x \Delta x_{t-1} + \epsilon_t \tag{2}$$

$$z_t = \rho^z z_{t-1} + \eta_t \tag{3}$$

The simplifying assumption is made that no information over the magnitude or direction of future productivity is contained in the productivity process a itself. To achieve this one has to choose the parameters of the underlying processes in such a way that the permanent and temporary component are impossible to disentangle as the future productivity path in response to shocks in opposite directions to the components cancel each other out. The product of a worker a_t then appears to be a random walk. These properties are achieved by choosing the following parameter relations for the permanent and temporary component following (Lorenzoni, 2011) and (Blanchard et al., 2013).

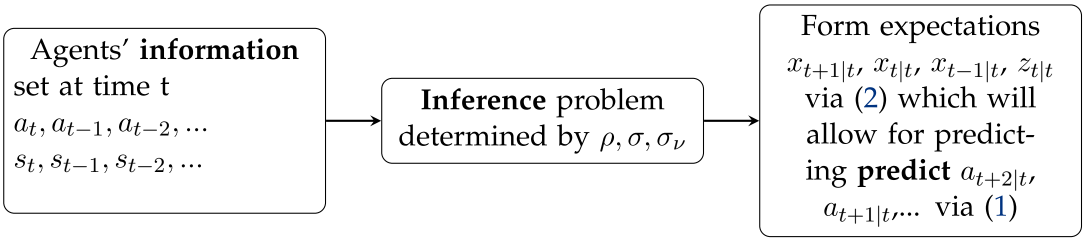


Figure 1: Information extraction problem

$$\rho^x = \rho^z = \rho \tag{4}$$

$$\rho\sigma_\epsilon^2 = (1-\rho)^2\sigma_\eta^2 \tag{5}$$

3.1.2 Information

Since only the present and past joint realizations of the permanent and temporary match productivity components $a, a_{t-1}, a_{t-2}, a_{t-3}, ...$ are part of the agents' information set in period t, it is impossible for agents to tell whether future match productivity will grow or decline just from observing the productivity process. All information that may help agents disentangle the permanent from the temporary process and thereby predict future match productivity growth is summarised in a signal in equation (6).

All agents in receive a noisy signal s_t informing them about the share of the permanent component in total match productivity, which allows for expected productivity growth forecasts. ν_t is independently, identically, and normally distributed noise shocks with mean 0 and constant and known variance σ_ν^2.

$$s_t = x_t + \nu_t \tag{6}$$

3.1.3 Forming expectations over future match productivity

All agents have the same information set and are assumed to know the distributions of shocks and form the productivity process takes. The agents information set consists of all past and present productivity realisations and past and present signals. Assuming agents observe the processes and signals over a long time this information problem is optimally resolved by rational agents with a converged Kalman filter.

If agents wouldn't receive an informative signal then the choice of parameters $\rho^x, \rho^z, \sigma_\epsilon^2, \sigma_\eta^2$ would have the consequence that expected future productivity would be equal to current productivity. Thus $E_t(a_{t+s}) = a_t$ for all $s \geq 1$ as the path of productivity is observed to be a random walk. However, agents receive a present signal. After convergence of the Kalman filter, there is no information in past signals beyond the best guesses derived past expected values of the permanent (x) and temporary (z) component of worker productivity a .

Due to agents receiving a signal over the permanent component of productivity x, and thus over the future growth of productivity to be expected, a signal extraction problem evolves. As in (Blanchard et al., 2013) this information extraction problem is solved with a typical agent Kalman filter closer described in Appendix A. Each element of the Kalman gain will be a function defined by the parameters $\sigma_\epsilon, \sigma_\nu$,$\rho^x$, and ρ^z.

$$K = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \\ K_{31} & K_{32} \end{bmatrix} = K(\sigma_\epsilon, \sigma_\nu, \rho^x, \rho^z) \tag{7}$$

The objective of the maximum likelihood estimation will be to estimate the parameters defining the Kalman gain in equation (7). Based on the estimated values of $x_{t|t}, x_{t-1|t}, z_{t|t}$ agents form their expectations over future productivity growth in each period.

$$a_t = x_{t|t} + z_{t|t}$$
$$E_t(a_{t+1}) = (1+\rho^x)x_{t|t} - \rho^x x_{t-1|t} + \rho^z z_{t|t}$$
$$E_t(a_{t+2}) = [(1+\rho^x)^2 - \rho^x]x_{t|t} - (1+\rho^x)\rho^x x_{t-1|t} + (\rho^z)^2 z_{t|t}$$

This convereges in the long-run to equation (8).

$$E_t(a_{t+\infty}) = \frac{x_{t|t} - \rho^x x_{t-1|t}}{1-\rho^x} \tag{8}$$

3.2 Household

There exists a large representative household, whose members maximize the present value of future expected utility and the instant utility function has a constant-elasticity of substitution specification.

$$\max_{g_t, c_t} E_t \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\zeta}}{1-\zeta} \tag{9}$$

subject to a budget constraint

$$c_t + g_t = (w_t n_t + d_t + b_t u_t + r_{t-1} g_{t-1}) = (a_t n_t - \kappa_t v_t + u_t b_t + g_t) \tag{10}$$

Here β is the discount factor, g_t are one period bonds r_{t-1} is the interest rate on bonds of the past period set in period $t-1$ and received in period t. The interest rate is defined as the equilibrium rate at which household members would be willing to lend to each other. w_t is the real wage, b_t is the value of household production for an unemployed worker, and d_t is the profit created by firms. The part after the second equal sign in the budget constraint follows from the aggregate resource constraint $w_t n_t + d_t = (a_t n_t - \kappa_t v_t)$.

As usual the first order conditions lead to the expected shadow value of the period budget constraint being $c_t^{-\zeta} = \mu_t$, where μ is the Lagrangian multiplier on the budget constraint. The inter-temporal Euler equation for bonds is $\mu_t = \beta r_t E_t(\mu_{t+1})$. We can rewrite this as equation (11).

$$\frac{1}{r_t} = \beta \frac{E_t(\mu_{t+1})}{\mu_t} \tag{11}$$

3.3 Production

Firms are assumed to be identical and to produce goods in period t according to $\prod_t = a_t n_t^{1-\alpha}$. In order to produce, firms have to hire workers in a labour market with matching frictions. The number of firms and workers that meet each other in every period is determined by the matching function $m(v_t, u_t) = m v_t^{1-\xi} u_t^{\xi}$.[1] m is a linear matching productivity parameter, v_t is the number of posted vacancies in a given period, and $u_t = 1 - (1-\lambda)n_{t-1}$ is the number of unemployed before matching occurs in a given period. Jobs are destroyed at the constant rate λ following the argument in (Shimer, 2012). Furthermore, it costs a firm κ_t to post a vacancy.

Firms are assumed to be small enough to take the matching probability $\frac{m(v_t,u_t)}{v_t} = q(\theta_t)$ as given. $\theta_t = \frac{v_t}{u_t}$ is a measure of labour market tightness. Firms are also assumed to be hiring in markets large enough compared to the number of workers they employ that the law of motion for employees for an individual firm corresponds to the law of motion of the labour market as a whole. Finally, the law of motion for the rate of employment is $n_t = (1-\lambda)n_{t-1} + m(v_t, u_t)$. Note that workers will take up production in the same period that they are hired. Furthermore, workers can be separated and re-employed in the same period, which means that there are more workers searching for a job in a current period than the number of unemployed $(1 - n_{t-1})$ in the previous period.

Firms will have to decide about how many workers to hire workers based on their expectations on present and future labour productivity. The firm's management then chooses v and n to maximize the value of expected profits discounted by the expected utility contribution of the production value, which in a model with a bond market would equal the interest rate.

$$\max_{v_t, n_t} E_t \sum_{t=0}^{\infty} \beta^t \mu_t (a_t n_t^{1-\alpha} - w_t n_t - \kappa_t v_t) \tag{12}$$

This value is maximised subject to the constraint in equation (13).

$$n_t = (1-\lambda)n_{t-1} + v_t q(\theta_t) \tag{13}$$

[1] I also use an alternative specification of the matching function $m(v_t, u_t) = \frac{v_t u_t}{(v_t^l + u_t^l)^{\frac{1}{l}}}$, which has the advantage of guaranteeing transition probabilities between 0 and 1 for any positive values of v and u, but requires bargaining power dependent on tightness θ to fulfill the Hosios condition.

ζ_t is the Lagrange multiplier put on the constraint in equation (13). Combining the first order condition for v_t, $\zeta_t q(\theta_t) - \mu_t \kappa_t = 0$, with the first order condition for n_t, $\mu_t(1-\alpha)a_t n_t^{-\alpha} - \zeta_t + (1-\lambda)\beta E_t(\zeta_{t+1}) = 0$ yields the job creation condition where the expected cost of hiring a new worker equals the benefit of hiring a new worker. ζ is the Lagrange multiplier on the law of motion for the individual firms.

$$\frac{\kappa_t}{q(\theta_t)} = (1-\alpha)a_t n_t^{-\alpha} - w_t + \beta(1-\lambda)E_t[\frac{\mu_{t+1}}{\mu_t}\frac{\kappa_t}{q(\theta_{t+1})}] \tag{14}$$

We can simplify (14) by substituting for r_t with (11). Firms and workers split the expected surplus of a successful match according to a Nash bargaining protocol with the firm's bargaining strength being π. The negotiated wage is in equation (15).

$$w_t = \pi b_t + (1-\pi)[(1-\alpha)a_t n_t^{-\alpha} + (1-\lambda)\frac{1}{r_t}E_t \kappa_{t+1}\theta_{t+1}] \tag{15}$$

Substituting equation (14) back into the job creation condition yields the job creation condition as a function of productivity, tightness, the outside value and the vacancy positing cost.

$$\frac{\kappa_t}{q(\theta_t)} = \pi((1-\alpha)a_t n_t^{-\alpha} - b_t) + (1-\lambda)\frac{1}{r_t}E_t[\frac{\kappa_t}{q(\theta_{t+1})}) - (1-\pi)\kappa_{t+1}\theta_{t+1}] \tag{16}$$

3.4 Equilibrium job creation and integrated match productivity

Equation (2) shows that the choice for the match productivity process is integrated to capture periods of expected match productivity growth with the permanent component. Combining this with the job creation condition in equation (16) provides two possible interpretations for the model. In the first interpretation, x captures labour productivity changes due to permanent shifts in the surplus provided by a match. This interpretation of x is referred to as the fundamental surplus (FS) interpretation in this paper. The second interpretation of x is to capture permanent changes in labour productivity leading to temporary deviations of the match product due to the catch-up of other factors defining the value of a match, concretely in this model the cost of posting a vacancy and the replacement rate. This allows for a constant long-run unemployment equilibrium with non-constant long-run productivity. This interpretation of x is referred to as the match productivity (MP) interpretation in this paper.

Note that the MP interpretation nests the FS interpretation for values of $\gamma_s = 0$ for all s, but both interpretations are important as they are able to capture news and noise regarding different features of the labour market. Therefore both versions of the model are implemented and estimated, but the (MP) focus is on the (MP) estimation, as noise is a more potent factor in the MP interpretation simulation and estimation results of the MP interpretation will be presented in Section 4, while estimation results capturing the noise component in the FS interpretation will be presented in Appendix C.

3.4.1 Match productivity interpretation (MP)

We can interpret x as a variable capturing labour productivity growth, with this labour productivity growth leading to a long-run stable Beveridge curve. A permanent increase in labour productivity would then permanently increase consumption and output, but would only lead to a temporary increase in employment. Thus it removes the unit root from the job creation condition in equation (16) by introducing other variables which lead to a de-trending similar to (Schmitt-Grohé and Uribe, 2012). It turns out that for the unit root to be removed from the fundamental surplus and to introduce a long-run unemployment equilibrium it is required that the cost of vacancy creation κ_t and the outside value to a match b_t catch up with match productivity a_t in the long-run. Arguments for a relatively stable job creation condition over time follow from the evidence regarding the stable Beveridge curve in (Martellini and Menzio, 2020).

We can then interpret the permanent labour productivity component similarly to a supply shock in (Blanchard and Quah, 1993). Using these long-run restrictions on a VAR(2) model with changes to labour productivity [FRED: OPHNFB] and the employment rate [FRED: 1-UNRATE] yields a positive temporary response of employment to a long-run labour productivity as shown in Figure 2. The model is supposed to create a similar response in the employment rate via increased job creation when output per worker permanently rises.

However, is proven that Proposition 1 holds, namely that when parameters κ_t and β_t depend on aggregate contemporary variables, such as output per worker, consumption, or wages, then a change in output per worker won't affect job creation. This is an extension of the neutrality result in (Shimer, 2010) in an equilibrium unemployment growth model in the spirit of (Pissarides, 2000) to expectations shifts in labour productivity.

Proposition 1. *Cost of vacancies κ_t and unemployment benefits b_t, which are proportional to contemporary variables such as output per worker, consumption, output, or wages in a plain Diamond-Mortensen-Pissarides random search DSGE model lead to labour productivity and expected labour productivity changes leaving the employment rate unaffected.*

Proof. Assume $\kappa_t = \psi_1 a_t$ and $b_t = \psi_2 a_t$. Here ψ_1 and ψ_2 are parameters, which could stand for κ and b. For simplicity set $\alpha = 0$ and $\zeta = 1$. Inserting these in the job creation condition means the job creation condition becomes equation (17).

$$\frac{\psi_1}{q(\theta_t)} = \pi((1-\alpha)n_t^{-\alpha} - \psi_2) + (1-\lambda)E_t[\frac{1}{r_t}\frac{a_{t+1}}{a_t}[\frac{\psi_1}{q(\theta_{t+1})}) - (1-\pi)\psi_1\theta_{t+1}]] \tag{17}$$

Note that $\frac{1}{r_t}\frac{a_{t+1}}{a_t} = \frac{c_t}{c_{t+1}}\frac{a_{t+1}}{a_t}$ and $c_t = a_t(n_t - \psi_1 v_t + \psi_2(1-n_t))$. Thus all changes and expected changes to the product of labour cancel out. Equivalent results can be achieved

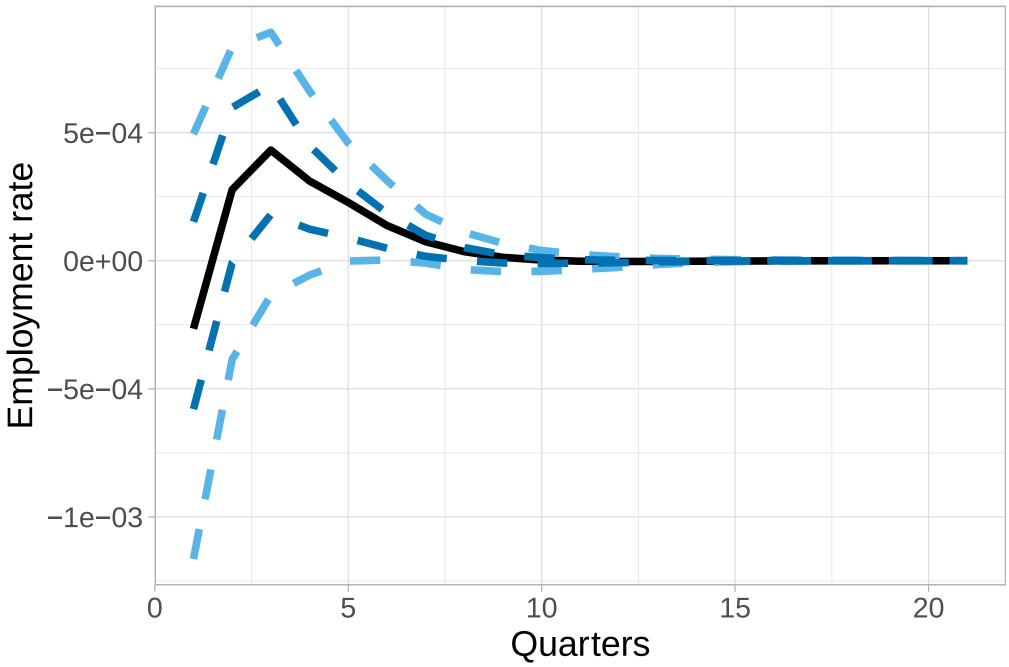


Figure 2: Response of the employment rate to labour productivity [OPHNFB] identified using long run restrictions following Blanchard and Quah (1993).

when using output per worker where $y_t = a_t \frac{n_t + \psi_2(1-n_t)}{n_t}$ or wages $w_t = a_t[\pi\psi_2 + (1-\pi)[1 + (1-\lambda)\psi_1 E_t(\theta_{t+1})]$. $\square$

To achieve the theoretical result of employment growth as a result of growth in output per worker, consistent with Figure 2 and Okun's law, which continues to fit the data (Ball, Leigh, and Loungani, 2013), it is necessary for current labour productivity to temporarily increase in proportion to vacancy cost and the unemployment benefit. Making both series dependent on past labour productivity realisations achieves this result with $\kappa = \kappa \prod_{s=1}^{L} a_{t-s}^{\gamma_s}$ and $b_t = b \prod_{s=1}^{L} a_{t-s}^{\gamma_s}$. The parameters γ_s control the importance of each lag. Assume $\sum_{s=1}^{L} \gamma_s = 1$, which is necessary for a stable equilibrium to exist. Dividing the job creation condition by $\prod_{s=1}^{L} a_{t-s}^{\gamma_s}$ shows that job creation and employment rate changes will depend on relative labour productivity in (18).

$$\Delta n_t \propto \frac{a_t}{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}} \tag{18}$$

We can rewrite then after taking logs this relative process as a sum of γ_s weighted changes.

$$\log\left(\frac{a_t}{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}}\right) = \left(\sum_{s=1}^{L} \gamma_s\right)\Delta a_t + \left(\sum_{s=2}^{L} \gamma_s\right)\Delta a_{t-1} ... + \gamma_s \Delta a_{t-s}$$

A regression of employment rate changes on past and present changes in output per worker my then reveal the relative importance of each lag. These regressions are shown in Table 1 and suggest that only the past two lags matter. Based on the model of the first column their relative size of γ_1 and γ_2 should be set at $\frac{\hat{\beta}_1+\hat{\beta}_2}{\hat{\beta}_1+2\hat{\beta}_2} = \gamma_1 = 0.697$ and $\frac{\hat{\beta}_2}{\hat{\beta}_1+2\hat{\beta}_2} = \gamma_2 = 0.303$ ($\hat{\beta}$ are the estimated values in Table 1). These values will be used in the calibration of the model with the labour productivity interpretation (MP) below.

3.4.2 Fundamental surplus interpretation (FS)

The alternative interpretation is that the permanent component x captures structural changes in the labour market, permanently changing the fundamental surplus as defined in (Ljungqvist and Sargent, 2017) generated by matched employed over unmatched unemployed. In this case we can choose a constant value for $\kappa_t = \kappa$ and $b_t = b$. This interpretation allows for capturing periods of different employment volatility in response to fundamental shocks and the expectation and noise around permanent unemployment equilibrium shifts.

3.5 Aggregate equilibrium and labour productivity as a hiring driving force

Market clearing in this simple setting requires that in this economy everything produced will be consumed.

$$c_t = a_t[n_t^{1-\alpha} - \kappa_t v_t + b_t(1-n_t)] \tag{19}$$

For both the FS interpretation and the MP interpretation this means that increases in the permanent integrated component x lead to permanent increases in the level of consumption. This is straightforward for the FS model but less straightforward for the MP interpretation. To see this for the MP interpretation assume for simplicity that $\prod_{s=1}^{L} a_{t-s}^{\gamma_s} = a_{t-L}$. This is the case when all but one value of γ_j are 0, and serves purely for making the illustration below easier and less heavy on notation. Further define $P_t = \frac{a_t}{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}}$. Equation (19) shows that, while long-run unemployment has an equilibrium level in this model in contrast to the simple model in (Blanchard et al., 2013), the qualitative long-run outcome of consumption in both models is the same as long as $n^* + bu^* > \kappa v^*$ in the steady-state. This inequality has to be fulfilled for any reasonable calibration of the search and matching model as otherwise, the matching process would cost more resources than the economy produces. Absent any permanent productivity shocks, the value long-run consumption will converge to $c_\infty = (n^* + bu^* - \kappa v^*)x_\infty = (n^* + bu^* - \kappa v^*)(\frac{x_t - \rho x_{t-1}}{1-\rho})$.

The remaining equilibrium equations for the five variables: $c_t, n_t, u_t, \theta_t, v_t$ are:

$$c_t/a_{t-L} = p_t n_t - \kappa v_t + b(1-n_t) \tag{20}$$

$$\frac{\kappa}{q(\theta_t)} = \pi(P_t - b) + \beta(1-\lambda)E_t[P_{t-L+1}\frac{c_{t+1}^{-\zeta}}{c_t^{-\zeta}}(\frac{\kappa}{q(\theta_{t+1})} - (1-\pi)\kappa\theta_{t+1})] \tag{21}$$

	Dependent variable:		
	$\Delta\_Employment\_rate$		
	(1)	(2)	(3)
$\Delta\_Output\_per\_worker$	0.194***	0.171***	0.194***
	(0.065)	(0.066)	(0.064)
$lag(\Delta\_Output\_per\_worker)$	0.149**	0.161**	0.149**
	(0.065)	(0.064)	(0.064)
$lag(\Delta\_Output\_per\_worker, 2)$	0.088	0.094	0.087
	(0.065)	(0.066)	(0.064)
$lag(\Delta\_Output\_per\_worker, 3)$		0.012	
		(0.064)	
$lag(\Delta\_Output\_per\_worker, 4)$		0.008	
		(0.064)	
$lag(\Delta\_Employment\_rate)$	-0.052	-0.081	-0.052
	(0.063)	(0.064)	(0.063)
$lag(\Delta\_Employment\_rate, 2)$	-0.002	-0.019	
	(0.064)	(0.065)	
Constant	-0.002***	-0.002**	-0.002***
	(0.001)	(0.001)	(0.001)
Observations	255	253	255
R^2	0.064	0.065	0.064
Adjusted R^2	0.045	0.039	0.049
Residual Std. Error	0.008 (df = 249)	0.008 (df = 245)	0.008 (df = 250)
F Statistic	3.406*** (df = 5; 249)	2.447** (df = 7; 245)	4.274*** (df = 4; 250)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 1: Ordinary least square regressions of changes to the employment rate [FRED: 1-UNRATE] on it's past values as well as past and present labour productivity [FRED: OPHNFB] measures.

$$n_t = (1-\lambda)n_{t-1} + v_t q(\theta_t) \tag{22}$$

$$u_t = 1 - (1-\lambda)n_{t-1} \tag{23}$$

$$\theta_t = \frac{v_t}{u_t} \tag{24}$$

3.5.1 Labour productivity as a hiring driving force

A closer examination of these equations shows that their equilibrium path is fully determined by the parameters $\beta, \lambda, \kappa, \pi, b, \zeta$, the value of employment in the previous period n_{t-1}, and the $L-1$ past, the expected current, as well as the expected future values of the product of a job $a_{t-L+1}, ..., a_{t-1}, E_t a_t, E_t a_{t+1}, ...$. The model can be linearised (see Appendix A) in the form where the optimal policy resulting in current labour market tightness is a function of the exogenous parameters (summarised by ψ_1 and ψ_2) and the expected path of future expected productivity and cost changes.

$$\hat{\theta}_t = \psi_1 = \psi_1 E_t \sum_{s=0}^{\infty} \psi_2^s \hat{P}_{t+s} \tag{25}$$

Here $\hat{P}_t$ is is the linearisation of $P_t = \frac{a_t}{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}}$ with all $\gamma_s = 0$ for the FS interpretation.

3.6 State space form

Combining the equations from Section 3.1.3, Section 3.5 and Appendix A allows representing the linearised model in a state-space form. The model has 7+2(L-1) state variables ($n_{t-1}, x_{t-1|t-1}, x_{t-2|t-1}, z_{t-1|t-1}, x_{t-1}, x_{t-2}, z_{t-1}, ..., x_{t-L}, z_{t-L}$) and one endogenous choice variable (θ).

$$AE_t \begin{bmatrix} \theta_{t+1} \\ n_t \\ x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ x_t \\ x_{t-1} \\ z_t \\ \cdots \\ x_{t-L+1} \\ z_{t-L+1} \end{bmatrix} = B \begin{bmatrix} \theta_t \\ n_{t-1} \\ x_{t-1|t} \\ x_{t-2|t} \\ z_{t-1|t} \\ x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ \cdots \\ x_{t-L} \\ z_{t-L} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{26}$$

The first two rows and columns of matrices A and B are given by the approximated market clearing equations. Meanwhile, the lower right parts of the matrices are a combination of the shocks driving the actual productivity series, which in turn together with the noise shock define the expectations about future productivity growth via the agent Kalman filter. The values in this lower part will be a function of the parameters of the productivity and noise process σ_ϵ, σ_ν, ρ^x and ρ^z. Estimating these parameters is the central aim of this model. As an example, in the case where $L = 1$ the number of state variables collapses to 7. The concrete implementation of this model is described in Appendix F.

4 Empirical evaluation of the model

The first subsection of this section describes the data used to empirically evaluate the model, while the subsequent subsections present calibration, simulation, and estimation results.

4.1 Data

The parameters defining the variance of news σ_ϵ and noise σ_ν in the labour market as well as the persistence of shocks ρ are estimated below by maximizing the likelihood given that the data was produced by a model with these specifications. An advantage of this empirical strategy is that it is not necessary for the econometrician to find a series that is informative about the signal that agents receive about future productivity. Instead one can base the estimation of the noise term on the observed outcomes in the labour market. Given that the aim of the model is to estimate the extent to which news and noise on future worker productivity influences labour market decision making, the parameters will only be identified if the model is estimated based on a series that informs about the productivity developments and a series that informs about aggregate labour market outcomes following these productivity changes. If worker productivity changes precede and accompany hiring then these movements in the labour market series are best explained as the result of surprise or news shocks. On the other hand, if workers are hired while their productivity in comparison to the outside value of employment remains unchanged, then these hires are most likely the result of noise. For the productivity series, changes in real output per worker is chosen. For labour market outcomes, both the job-finding rate ($p(\theta_t)$), and the unemployment rate may be good variables for identifying the parameters of the shocks. Estimating based on unemployment outcomes has the advantage that the series is directly observed and the potential measurement error is therefore less. On the other hand, estimating a perturbed model based on transition probabilities has the advantage of ensuring that the probabilities are within the bounds 0 and 1, as required by the theoretical setup of the model. However, transition probabilities are not directly observed and have to be constructed which may lead to a bias or a larger measurement error of the series. As there are advantages and disadvantages to either series the model is estimated alternatively based on unemployment, based on the job-finding rate.

The concrete series for labour productivity changes used is the output per worker series computed by the BLS with the FRED code OPHNFB. The series is similar to the raw real output per worker series as can be seen in Figure 3. The unemployment rate is taken from the data, and the job-finding probability p is computed from monthly data and then aggregated to quarterly data following (Shimer, 2005). Further descriptions and discussions about the data used can be found Appendix B.

4.2 Calibration of the model

The model is calibrated to reflect employment and job-finding rates in the US labour market. Based on monthly data between 1949 and the end of 2019 the average unemployment rate for the US was 6.5%. The average monthly job-finding probability was 0.41 (see section 4.1). If we assume that the mean is a close reflection of the steady-state equilibrium rate then it follows that $u = \frac{\lambda}{\lambda + p(\theta)}$, and that 0.0262 is a good guess for the monthly separation rate - a value that is in agreement with (Hagedorn and Manovskii, 2008). The quarterly job-finding rate is then $1 - (1 - 0.41)^3 = 0.79$. Taking the assumed law of transition in the model, this corresponds to a quarterly separation rate λ of 0.269. Thus about half of the jobs are created only in the past six months. This may seem like a high value, but under the model assumptions, 81% of the workers are rematched within the same period in steady-state and are thus productive. The 25% destroyed jobs, therefore, include job to job transitions. The observed quarterly flow from employment to unemployment is only 5%, which is broadly in line with the empirically estimated values found in the literature. (Den Haan, Ramey, and Watson, 2000) find that the quarterly vacancy filling rate for the second quarter of 1972 to the 4th quarter 1988 was 0.71. The quarterly job-finding rate for this sample was on average 0.81. The values can therefore be assumed to be close to the steady-state. steady-state labour market tightness is then estimated to be $\theta = \frac{p(\theta)}{q(\theta)} = 1.141$.

Calculating the rate of vacancy postings as a proportion of the labour force in as measured by the JOLTS for the available sample (December 2000 - December 2017) yields 0.02647. Dividing this by the estimate for the unemployment rate for the sample yields a labour market tightness of 0.425. Dividing the sample job-finding rate 0.328 by this result yields a monthly vacancy filling rate of 0.77. The quarterly job-finding rate is then 0.696 and the vacancy rate 0.988. Given the assumption of the matching function one can then estimate the parameters of the constant elasticities of the transition functions as $\frac{p(\theta)-p(\theta')}{q(\theta')-q(\theta)}\theta \approx \frac{1-\xi}{\xi}$ Then the estimate for the matching elasticity is $\xi \approx 0.7356$. This value is close to the value used in (Shimer, 2005), which is 0.7. I choose 0.7 as a reasonable parameter for the elasticity of the vacancy filling. Based on this result the estimated value of the matching productivity parameter is $m = 0.695$. (Hagedorn and Manovskii, 2008) estimate that the cost of posting a vacancy costs 47.4% of the weekly product of labour. The quarterly product of labour in the steady-state is normalized to 1 in the model. This means a cost of vacancy posting κ of 0.0362. Given this, the value of home production should be set to $b = 0.8825$ to match the unemployment moment. Worker bargaining power is chosen such that it is socially efficient, which requires that it fulfils the Hosios condition ((Hosios, 1990)) $\xi = 1 - \pi$. For robustness, I employ two different calibrations which are matching the labour market

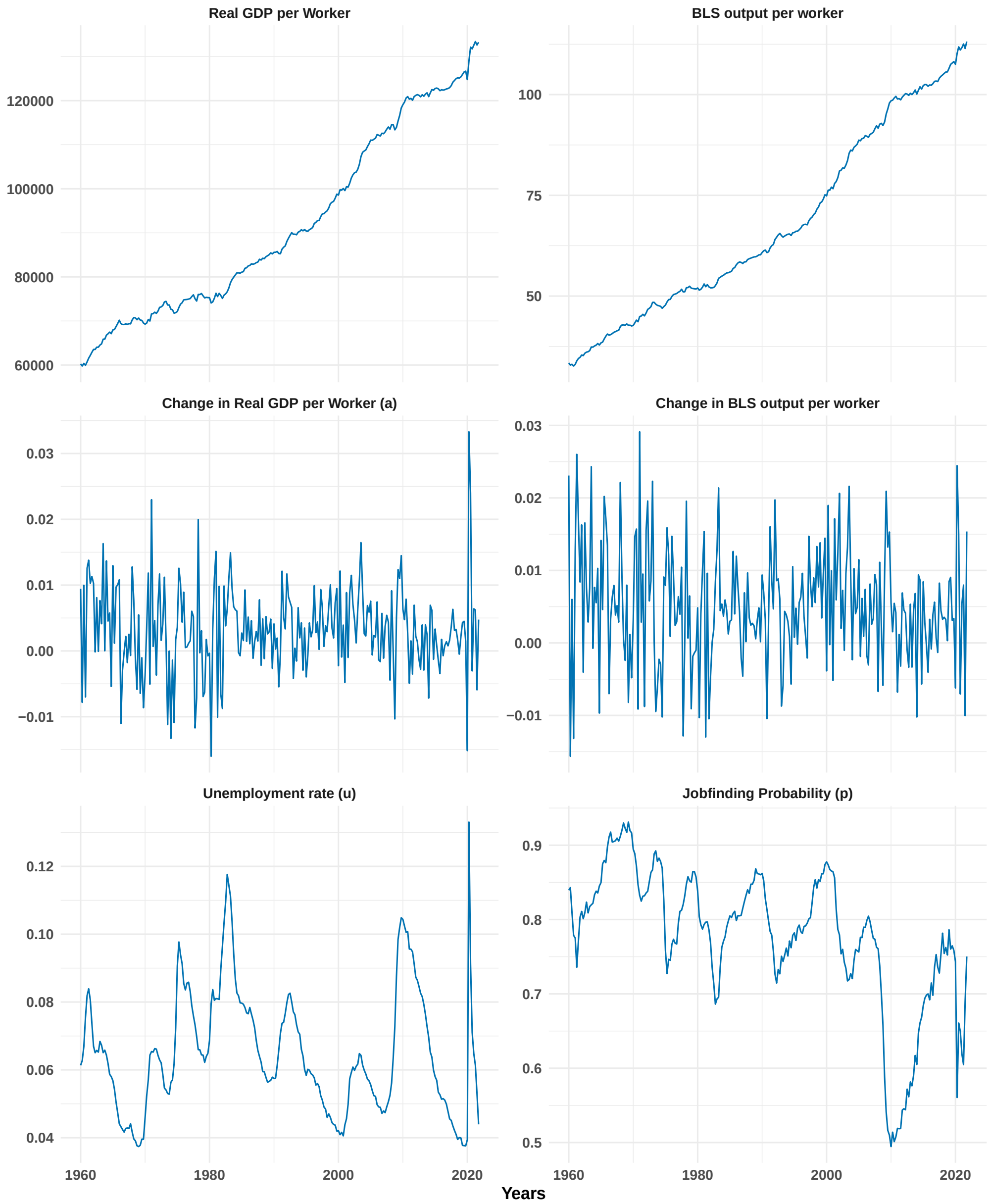


Figure 3: Data series used in the maximum likelihood estimation of the DSGE model. Source: Federal Reserve Economic Data (FRED)

Parameter	Value	Description
β	0.99	Discount rate.
α	0.66	Labour share.
ζ	1	Inter-temporal elasticity of substitution
m	0.77	Parameter of the matching function (match productivity)
κ	see Table 3	Cost of posting vacancies for firms.
b	see Table 3	Replacement rate for unemployed.
ξ	0.7	Parameter determining matching frictions, following (Lubik, 2009) and (Petrongolo and Pissarides, 2001)
λ	0.269	Chance of exogenous match separation.
ρ	0.9	Chance of exogenous match separation.
σ_ϵ^2	0.0001	Volatility of the permanent component.
σ_ν^2	0.0121	Volatility of noise.

Table 2: Parameters for the simulation.

Replacement rate b			Vacancy posting cost κ		
Baseline	Shimer	Intermediate	Baseline	Shimer	Intermediate
0.8825	0.4	0.6	0.0365	0.144	0.1

Table 3: The parameters varied for robustness for the simulated impulse response.

moments equally well. The first is the (Shimer, 2005) calibration which states $b = 0.4$ and uses chooses a value of κ to match unemployment. In this case the appropriate value of $\kappa = 0.144$. Finally, I employ an intermediate calibration between these two extremes with the replacement rate $b = 0.6$ and the vacancy posting cost $\kappa = 0.1$. These three calibrations are all able to produce a mean unemployment rate of 6.5% and a mean job-finding rate of 0.79. The calibration is summarised in Table 2 and Table 3.

(Lubik, 2009)). However, the chosen matching elasticity of 0.7 is on the upper end of the matching elasticities suggested by (Petrongolo and Pissarides, 2001)

4.3 Simulated impulse response

First, it is important to note that a shock to the permanent component ϵ, a shock to the temporary component η, and a noise shock ν will have different impacts on current labour productivity a_t as well as actual a_{t+s} and expected $E_t(a_{t+s})$ paths of future labour productivity. Figure 4 plots the actual path of labour productivity a_{t+s} in black. Note that a positive shock to the permanent component ϵ will permanently lift $a = x + z$ as x is permanently increased, capturing depending on the interpretation increases in the match surplus or match productivity. Meanwhile, a shock η lifting z will only have a transitory effect, while a noise shock ν will leave actual a unchanged. The share of noise σ_ν^2 in the signal is varied between half and four times its baseline value with lighter blue lines representing larger values of σ_ν^2. The dashed lines show the expectation of long-run productivity $E_t(a_{t+\infty})$. Note that a shock to ϵ with higher noise will mean expectations are slower upward adjusted. An η shock also means positive future expectations of $E_t(a_{t+\infty})$

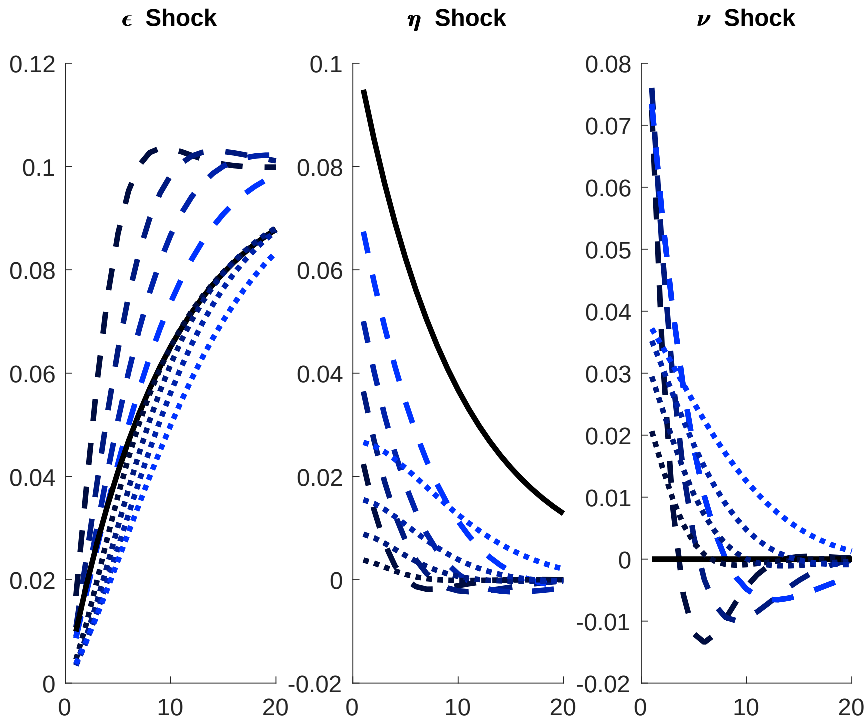


Figure 4: Comparison of a different strength of noise in the signal σ_ν^2 on the impulse response of actual a_t (black and solid), expected permanent productivity $x_{t|t}$ (dotted) and long-run expected productivity $E_t(a_{t+\infty})$ (dashed). Series with lighter blue represent larger values of σ_ν keeping σ_ϵ fixed.

especially when the noise is large. This is because a and the signal are the two observable series in the agent Kalman filter. When a rises due to an η shock agents may falsely conclude that the permanent component x has risen spelling a period of labour productivity growth rather than decline back to the original level. The noise shock leads to agents adjusting their expectations of long-run productivity rapidly upwards when noise is large and keeping them elevated. Finally, the dashed line shows the expectation of the current permanent component $x_{t|t}$. This is one of the state variables in the model. The simulations shock that a larger noise component will lead to a slower adjustment of expectations $x_{t|t}$ to actual x when it actually is shocked, and a larger falsely expected rise $x_{t|t}$ when it remains unchanged.

Figure 5 shows that a higher noise component will lead to a less aggressive hiring response to a rise in the permanent component x due to an ϵ shock in the MP version. Notably, employment will return to a long-run equilibrium following a shock. This is different in the FS version where an increase in the permanent component leads to a permanent increase in match surplus. This version is presented in Appendix C. The employment response to shocks to the temporary component is very similar across noise levels. Meanwhile, Figure 5 shows that a higher noise component can significantly drive the hiring rate with noise shocks potentially leading to a significant contribution in the short run variance of

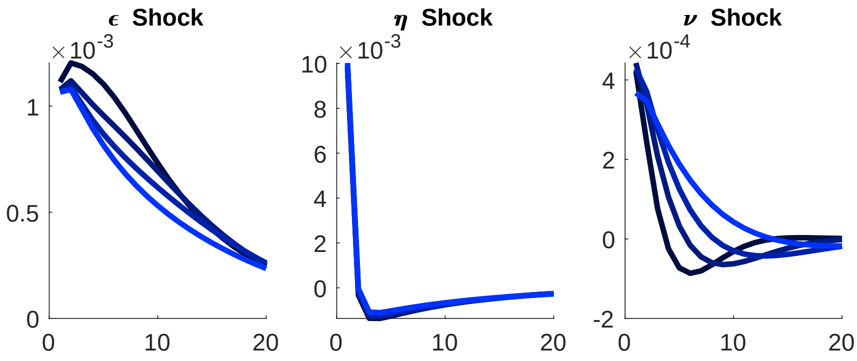


Figure 5: Comparison of a different strength of noise on the employment rate n with darker blue representing a smaller noise component for the MP interpretation.

the employment rate. The maximum likelihood estimation makes use of these different responses of productivity and employment rates in Figure 4 and Figure 5 to estimate the extent to which noise plays a role in aggregate job creation.

The impulse response functions of other variables of the model have been simulated with the parameters in Table 2, which result in an equilibrium employment rate of 93.5% in equilibrium. Similar to (Den Haan et al., 2000) the payments necessary to create a new job (κ) are interpreted as investment. The Figures below show the impulse response functions of labour productivity (a), employment (n_t), the job-finding rate ($p(\theta_t)$), consumption (c_t), labour market tightness (θ_t), and investment ($\kappa_t v_t$) for the different type of shocks employing the MP interpretations. Figures with the FS interpretation can be found in Appendix C. The different colours represent the three different calibrations with the main calibration being blue, the calibration following (Shimer, 2005) in green and the intermediate calibration in orange. The variance of the permanent component and the noise shock have been set to equal levels.

Figure 6 shows the impulse response function to a 1% shock to the permanent component x_t, while Figure 7 shows the same for z_t and Figure 8 for s_t as a result of a noise shock ν_t. The top graph shows the FS implementation, while the bottom the MP implementation. Both are estimated in Section 4.4.

4.3.1 A shock ϵ to the permanent component x of a

Figure 6 shows that a shock to the permanent component resulting in positive news about current and future productivity growth can capture the Pigou cycles in response to news shocks found in the data. As a is rising employment and job creation and investment shares will temporarily be elevated, while total consumption will increase permanently. The baseline calibration will lead to a stronger response due to the higher responsiveness of the match surplus to shocks as would be expected given the discussion in (Ljungqvist and Sargent, 2017). The reason for this responsiveness is that the steady-state match sur-

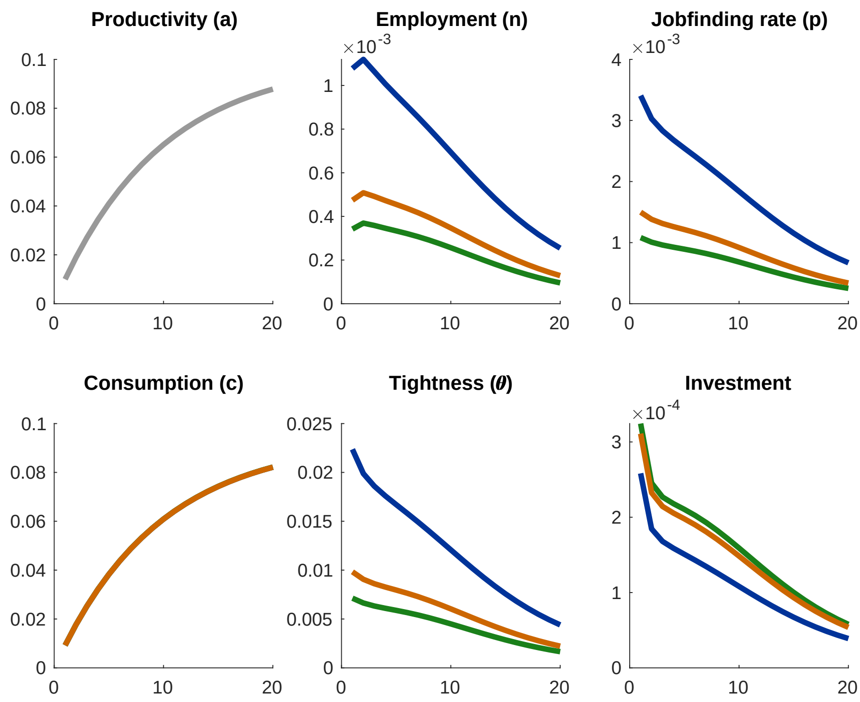


Figure 6: Responses to a shock to the permanent component (ϵ) in the MP implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

plus is smaller in the baseline calibration than in the Shimer or intermediate calibration. The increase in unemployment as growth stagnates produced by this model is coherent with the empirical observations that led to the formulation of Okun's law ((Okun, 1963)). In this process of declining employment, productivity growth will stagnate, but consumption growth will continue due to marginal increases in productivity and due to the decrease in investment and as fewer vacancies are being posted.

4.3.2 A shock η to the temporary component z of a

With regard to a shock to the temporary component z_t in period 0, a similar forces are at work as shown in Figure 7. In period 0 a surprise shock increases worker productivity and thereby output and consumption. Given the higher observed productivity value, agents form expectations over the permanent component and therefore the long-run value of a filled vacancy. Even though agents receive no signal that the permanent component has increased, they assume that the signal might have been drowned out by noise especially when the noise component is large. This may lead to elevated hiring beyond the initial period as long-run productivity expectations rise. In the MP implementation, the catch-up of the cost of posting a vacancy and the replacement rate will lead to the value of a match rapidly declining making the rise in employment in response to the shock brief. In the FS implementation in Appendix C the temporary shock will lead to a temporary increase

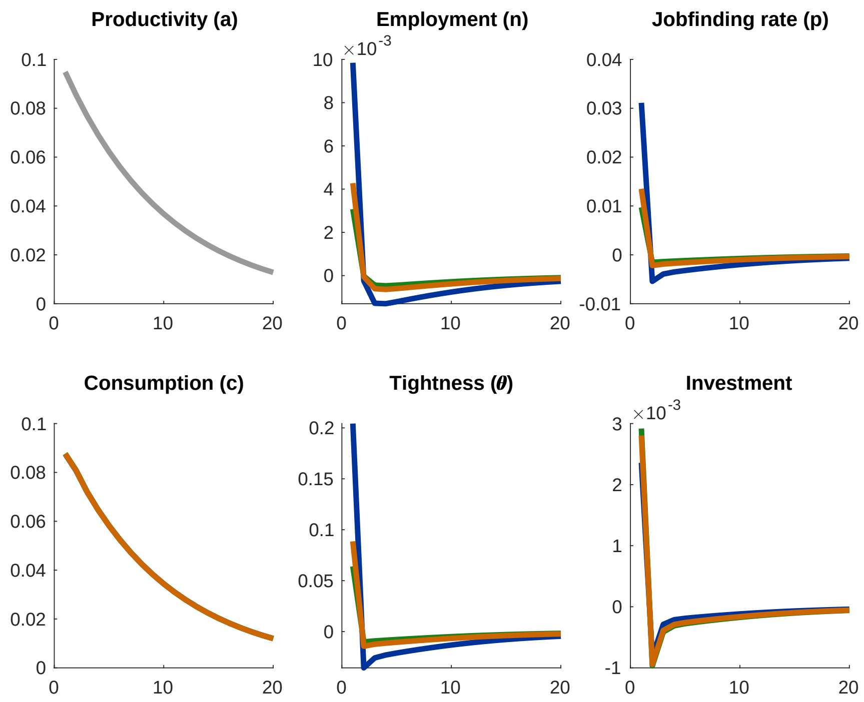


Figure 7: Responses to a shock to the temporary component (η) in the MP implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

in the match surplus making the response similar to the responses to a permanent shock in Figure 6 in the MP implementation. Note that with higher noise it becomes harder and harder for firms to separate the temporary from the permanent increase, which would lead to both impulse responses becoming flatter.

4.3.3 A shock ν to the noise in signal s

Figure 8 finally shows the impulse response functions caused by a noise shock. Actual worker productivity remains flat, but the noise shifts the expectation over the size of the long-run component x_t. The reason that agents do not observe the supposed shock to x_t in an increase in a_t could be due to a negative shock to the temporary component η_t occurring at the same time. Consequently, due to the change in expectations about the growth in the product that a worker-firm relationship will produce the firm's management will increase job postings. This will lead to a positive response of employment, output, investment and the job-finding rate in the period of the noise shock. Consumption will fall in the very short-run. The reason for this is a combination of efficient matching as the Hosios condition is fulfilled, and the increase in investment necessary to create the new jobs. As agents become consequently more certain in the following periods that the shock was noise, and the expected value of long-run productivity even falls below the equilibrium value before returning to equilibrium, firms drastically reduce hiring leading

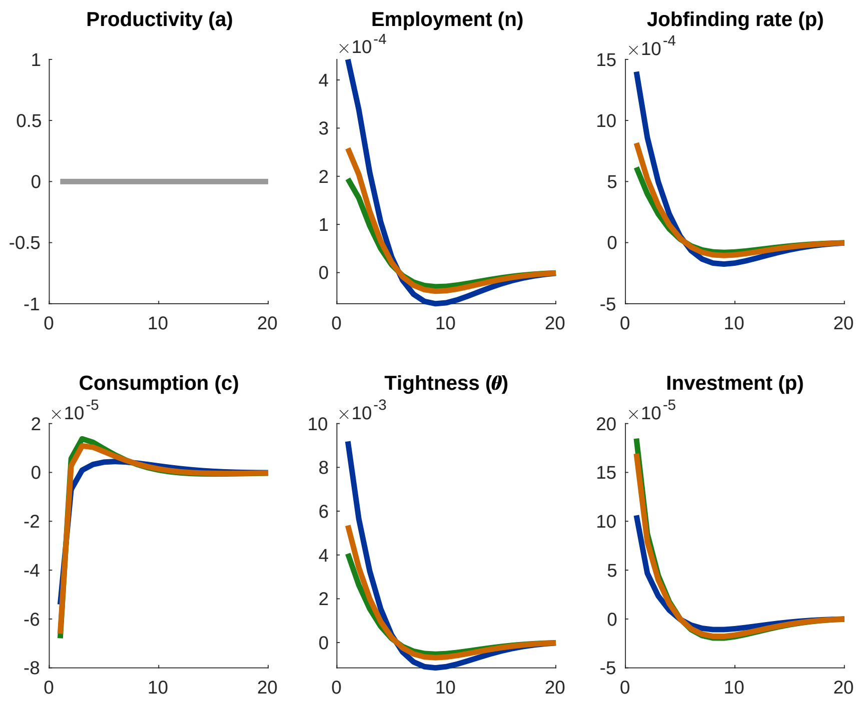


Figure 8: Responses to a shock to the noise shock (ν) in the MP implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

to a decrease in employment and an increase in consumption.

Interestingly, for both the MP and FS implementation (Appendix C) the reaction to a noise shock are similar. This is because the economy actually does not move in terms of fundamentals from its current state in either case and hiring and consumption movements are due to information misleading agents.

4.3.4 Variance decomposition of the simulation

The variance decomposition in Table 4 shows that under the baseline calibration noise may contribute substantially to employment fluctuations due to expected improvements in labour productivity in the short-run. The impact of noise is stronger in calibrations with lower b and higher κ as a higher cost of posting vacancies will increase the benefit of firms searching before expected labour productivity increases are realised. A quicker catching up and reduction of the fundamental surplus will lead to noise becoming a more substantial driver in the short-run for the same reasons. Noise has been chosen to have close to maximal impact in this calibration at $\sigma_\nu^2 = 0.0121$, which is achieved at $\frac{1-\rho}{\sqrt{\rho}}$. The simulation shows that noise can in the short run be a substantial driver of job creation. Under the MP interpretation with a long-run unemployment equilibrium noise contributes up to 24.47% to the short-run variation of employment relative to news from ϵ shocks. Noise impacts may even be higher if the assumption about current productivity knowledge is

Calibration	*Quarters*	1	2	3	4
	Match productivity interpretation				
Baseline	Noise (ν)	14.4300 %	8.38 %	3.68 %	1.08 %
	Permanent (e)	85.57 %	91.62 %	96.32 %	98.92 %
Intermediate	Noise (ν)	22.84 %	13.86 %	6.26 %	1.87 %
	Permanent (e)	77.16 %	86.14 %	93.74 %	98.13 %
Shimer	Noise (ν)	24.47 %	14.99 %	6.82 %	2.05 %
	Permanent (e)	75.53 %	85.01 %	93.18 %	97.95 %

Table 4: Relative variance decomposition of noise and expected permanent labour productivity or fundamental surplus improvements with regard to the employment rate based on a simulation with a large noise impact.

dropped and the signal and past observations determine current productivity expectations and firms hire based on these expectations. These simulations and the variance decomposition including the temporary shock can be found in Appendix C.

4.4 Estimation of the model

The maximum likelihood estimation of the model is based on the demeaned productivity series for output per worker, and the unemployment or job-finding rate as described in Section 4.1. Even though there are three innovations using the Kalman smoother estimation will only be successful based on two observable series at once as there are only two independent innovations in the form of productivity and noise shocks due to the parameter restrictions on the temporary and permanent components z and x. Only the parameters of the news and noise processes are estimated, while the labour market parameters are set via the calibration above. Two series cannot be expected to contain enough information to identify parameters such as the matching cost κ or b together with the shock parameters. For this reason, instead the three calibrations of the model presented in the simulation are estimated. The noise component around x is estimated both for the FS and MP implementation.

Figure 9 shows the results of the maximum likelihood estimation for the MP implementation. The results of the FS implementation of the estimation are in Appendix C. Table 5 shows the results and table Table 6 shows the corresponding variance decomposition for the estimation based on unemployment changes. The estimations of both implementations merely differ in terms of the size of volatility of σ_ϵ, which is to be expected as a calibration with lower b requires a higher volatility of structural shocks (Shimer puzzle). Noise is much smaller than σ_ϵ in any of the estimations meaning it is from every perspective and with every calibration an unlikely driver of employment changes and job creation. This holds true both in the FS implementation and in the MP implementation.

The estimations suggest that on the occasions on which agents receive information about the future, the information is usually precise. Thus, agents react rapidly to changes in the expected future productivity of a worker-firm relationship. There is little to no noise in the

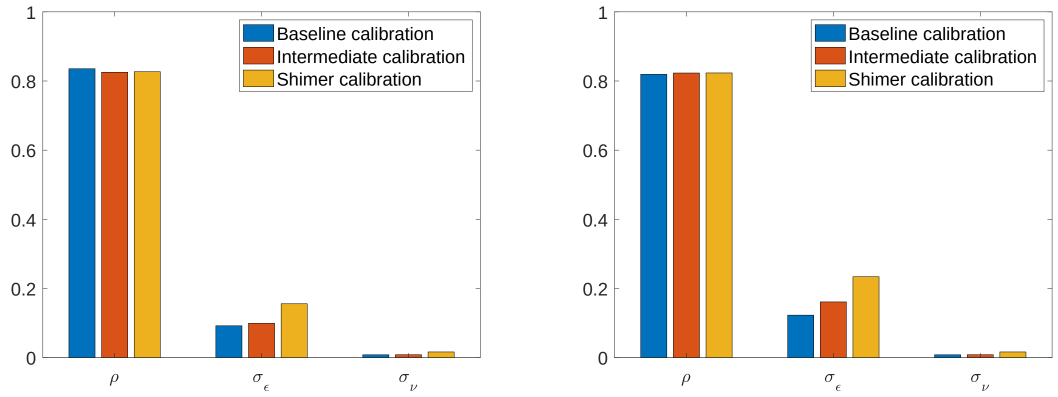


Figure 9: Results of the maximum likelihood estimation of the model in the MP implementation. Estimation results based on the unemployment rate are on the left, while estimation based on the job-finding rate are on the right.

Parameter estimated:	MP (Δa_t & Δu_t)	MP (Δa_t & $\Delta p(\theta_t)$)
ρ	0.8252 [72.5]	0.8193 [73.8]
σ_e	0.0922 [19.4]	0.1229 [23.7]
σ_ν	0.0083 [2.1]	0.0083 [0.6]

Table 5: Baseline estimated news and noise parameters by implementation with the series based on which the ML estimation was done in round brackets and the t-values in square brackets.

Calibration	*Quarters*	1	2	3	4
	Match productivity interpretation				
Baseline	Noise (ν)	0.1 %	0.05 %	0 %	0 %
	Permanent (e)	99.9 %	99.95 %	100 %	100 %

Table 6: Estimation based of relative variance decomposition of noise and expected permanent labour productivity or fundamental surplus improvements with regard to the employment rate.

signal on future worker productivity and barring surprise productivity shocks, the output that a worker will contribute to the economy is close to perfectly anticipated by agents. Fluctuations in employment are found to be likely the result of news and surprise shocks with noise shocks playing only a limited or no role in the labour market. It is thereby shown to be unlikely that spontaneous changes in labour demand are a significant driver of aggregate job creation.

5 A structural VAR estimation of noise in job creation

(Forni et al., 2017) suggest alterations to the assumptions taken in (Blanchard et al., 2013) to study the reaction of consumption to noise and news in a VAR model. If these assumptions hold, then it is possible to identify noise shocks with a structural VAR model. The proposed identification is implemented in this section as a method of further examining the plausibility of the results of the DSGE model present in previous sections. The most important change in the assumptions in (Forni et al., 2017) is that agents learn with certainty after a number of periods whether a past signal was news or noise. In contrast, in (Blanchard et al., 2013) agents only ever know with an increasing probability the true nature of past shocks. If agents are able to retrospectively identify noise shocks, then the econometrician will also be able to identify the shocks from the data reflecting the choices of the agents, provided that some reliable instrument for the signal based on which agent expectations are formed is available to the econometrician.

5.1 Relating the VAR model to the DSGE model

The process determining worker productivity is assumed to be a random walk with a drift τ.

$$a_t = a_{t-1} + \tau + \epsilon_{t-S} \tag{27}$$

ϵ_{t-S} is a news shock determined by a finite number of periods S in the past.

This process is related but not the same as the productivity process described in Section 3.1, where $a_t = x_t + z_t = (1+\rho)x_{t-1} - \rho x_{t-2} + \rho z_{t-1} + e_t + \eta_t = \rho a_{t-1} + x_{t-1} - \rho x_{t-2} + e_t + \eta_t$. If ρ is either 0 or 1 and in the second case the permanent component is not subject to shocks then the properties of the two processes are similar and the only difference is the timing of the signal. In the first case the result would be $a_t = x_t = x_{t-1} + \epsilon_{t-S}$, where $e_t + \eta_t = \epsilon_{t-S}$. In the second case $a_t = a_{t-1} + \eta_t = \epsilon_{t-S} = L^S \epsilon_t$.

As in Section 3.1 in each period agents are assumed to observe worker productivity a_t and to receive a noisy signal over future innovations as shown in equation (28).

$$s_t = \epsilon_t + \nu_t \tag{28}$$

There is assumed to exist a cointegrated relationship between the present discounted utility value of a filled vacancy and the value of unemployment. This renders the relative value of a filled vacancy P_t a stationary process, which is assumed to be the de-trended process a_t.

$$\Delta a_t = \Delta a_t - \tau = L^S \epsilon_t \tag{29}$$

The agents are assumed to know that both ϵ_t and ν_t are mean zero normally distributed and uncorrelated with each other and with previous and future realizations. The future expected values of productivity are then simply projections from e_{t-S} on s_{t-S}. Thus if I_t is the information set of agents at period t then productivity changes in the future can be extracted from the signal according to equation (30).

$$E(\Delta P_{t+1}|I_t) = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} s_{t-S} \tag{30}$$

It follows that the expected long-run change in the value of productivity is the sum of current productivity and the projections from the at time t available signals on future productivity shocks. This is described by equation (31).

$$E(P_{t+\infty} - P_t|I_t) = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} \sum_{i=0}^{S} s_{t-i} \tag{31}$$

Given the equilibrium described in Section 3.5 and the state space form discussed in Section 3.6 it becomes straightforward to form equations for approximating the labour market described above. Both labour market tightness and the job-finding rate will be a function of the equilibrium value plus deviations to the employment equilibrium in the previous period plus expected deviations of the relative value of the firm-worker relationship, plus an error term to capture exogenous shocks such as shocks to matching productivity.

$$\theta_t = \theta^* + \phi_{0,1}(n^* - n_{t-1}) + E_t \sum_{i=0}^{\infty} \phi_{0,2+i} \Delta p_{t+1+i} + e_{3,t} \tag{32}$$

Labour market tightness can be proxied for by the observed job-finding rate.

$$p(\theta_t) = p(\theta^*) + n^* + \phi_{1,1}(n^* - n_{t-1}) + E_t \sum_{i=0}^{\infty} \phi_{1,2+i} \Delta p_{t+1+i} + e_{3,t} \tag{33}$$

Finally using equation (34) in equation (33).

$$p(\theta_t) = p(\theta^*) + n^* + \phi_{1,1}(n^* - n_{t-1}) + \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} \sum_{i=0}^{S} \phi_{1,2+i} L^i s_t \tag{34}$$

Here θ^* and n^* are constants and expected to be the steady-state values when no productivity shocks occur. $e_{3,t}$ captures other shocks to the job-finding rate such as shocks to matching productivity. Finally, the law of motion of employment, or of unemployment can be captured by the equation (35).

$$n_t = n^* + \phi_{2,1}(n^* - n_{t-1}) + \phi_{2,2}(p(\theta^*) - p(\theta_t)) + e_{4,t} \tag{35}$$

The structural VAR system is then found in equation (36).

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{-\sigma_\epsilon^2}{\sigma_\epsilon^2+\sigma_\nu^2}\sum_{i=0}^{S}\phi_{1,2+i}L^i & 1 & 0 \\ 0 & 0 & \phi_{2,2} & 1 \end{bmatrix} \begin{bmatrix} \Delta P_t \\ s_t \\ p(\theta_t) \\ n_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ p(\theta^*) + \phi_{1,1}n^* \\ (1+\phi_{2,1})n^* + \phi_{2,2}p(\theta^*) \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\phi_{1,1} \\ 0 & 0 & 0 & -\phi_{2,1} \end{bmatrix} \begin{bmatrix} \Delta P_{t-1} \\ s_{t-1} \\ p(\theta_{t-1}) \\ n_{t-1} \end{bmatrix} + \begin{bmatrix} L^S & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \nu_t \\ e_{3,t} \\ e_{4,t} \end{bmatrix} \tag{36}$$

This model has a clear ordering. The job-finding rate will affect employment contemporaneously, but not vice versa. This ordering is used in the short-run restrictions imposed in Section 5.2.

5.2 Identification and estimation of the effect of noise

To estimate the model the difference of the two labour market series $p(\theta_t)$ and (n_t) is taken. Further, an instrument is chosen to measure the signal that is not observed directly. (Barsky and Sims, 2012) have suggested using the series in the Surveys of Consumers by the University of Michigan as instrument for future productivity expectations. The paper follows this suggestion with the chosen instrument z_t being the expectation of business conditions in a year from the Surveys of Consumers. The original question for the data series is "*And how about a year from now, do you expect that in the country as a whole, business conditions will be better, or worse than they are at present, or just about the same?*". Given this question, it is reasonable to assume that S=4, thus the measured signal informs about the news shock four quarters ahead. The signal series is shown in Figure 10. The series for output per worker, the job-finding rate and the employment rate are the same as the ones used for the estimation of the DSGE model and described in Section 4.1.

$$\begin{bmatrix} \Delta P_t \\ z_t \\ \Delta p(\theta_t) \\ \Delta n_t \end{bmatrix} = \sum_{i=1}^{4} A_i \begin{bmatrix} \Delta P_{t-i} \\ z_{t-i} \\ \Delta p(\theta_{t-i}) \\ \Delta n_{t-i} \end{bmatrix} + \begin{bmatrix} u_t \\ s_t \\ x_{3,t} \\ x_{4,t} \end{bmatrix} \tag{37}$$

The empirical strategy for identifying noise follows (Forni et al., 2017). It is assumed that there exists a fundamental representation of the system and a simple VAR with a four period lag is run to find the reduced form estimates as shown in equation (37). Here u_t is a surprise shock. s_t is a change in the signal. Meanwhile x_3 and x_4 are separate shocks

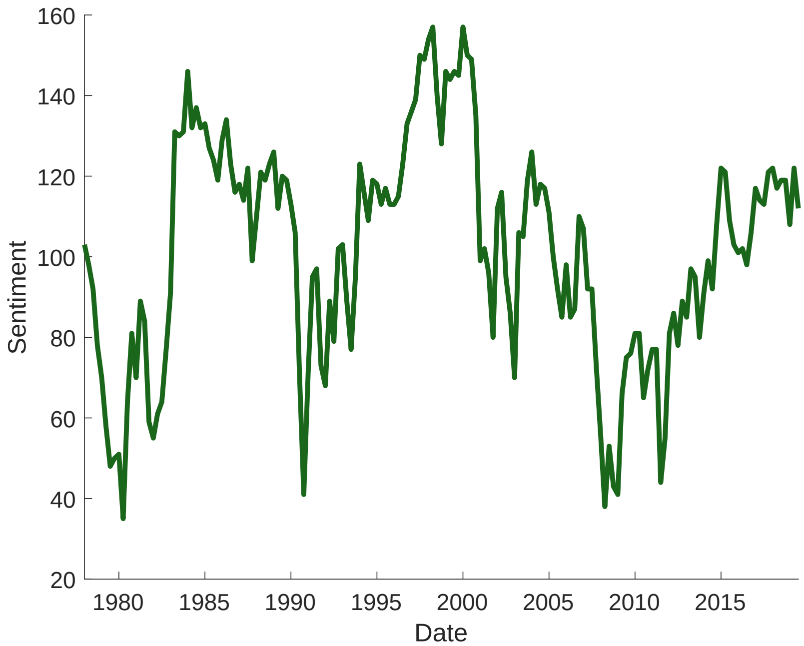


Figure 10: Surveys of Consumers by the University of Michigan index capturing business conditions for the next year.

that may also affect the observed variables and may be a combination of the shocks e_3 and e_4 described above. The moving average representation is then computed as in equation (38) and impulse response functions of the model are computed by imposing short-run restrictions keeping the original ordering.

$$\begin{bmatrix} \Delta p_t \\ z_t \\ p(\theta_t) \\ n_t \end{bmatrix} = \sum_{i=0}^{\infty} \tilde{A}_i L^i \begin{bmatrix} u_t \\ s_t \\ x_{3,t} \\ x_{4,t} \end{bmatrix} \tag{38}$$

The impulse response functions of the model with short-run restrictions are shown in Section 5.2 from the first period following the shock. As we would hope the signal predates the change in productivity and is briefly followed by a likely change in ΔP. Both positive shocks also lead to increases in the signal series, as well as increases in the job-finding rate and the employment rate as would be expected. Note that the signal shock seems to be having a stronger effect suggesting a possibly strong news or noise component in hiring.

(Forni et al., 2017) suggest that the structural shocks ϵ_t and v_t for fundamental news and non-fundamental noise can be recovered from the shocks of the reduced form representation u_t and s_t by using the structural assumptions made regarding the signal and rotating the VAR residuals to productivity and the signal instrument accordingly. Naturally, this method assumes that the structural assumptions in Section 5.1 correctly describe the actual process. The relation between the structural shocks and the fundamental shocks is

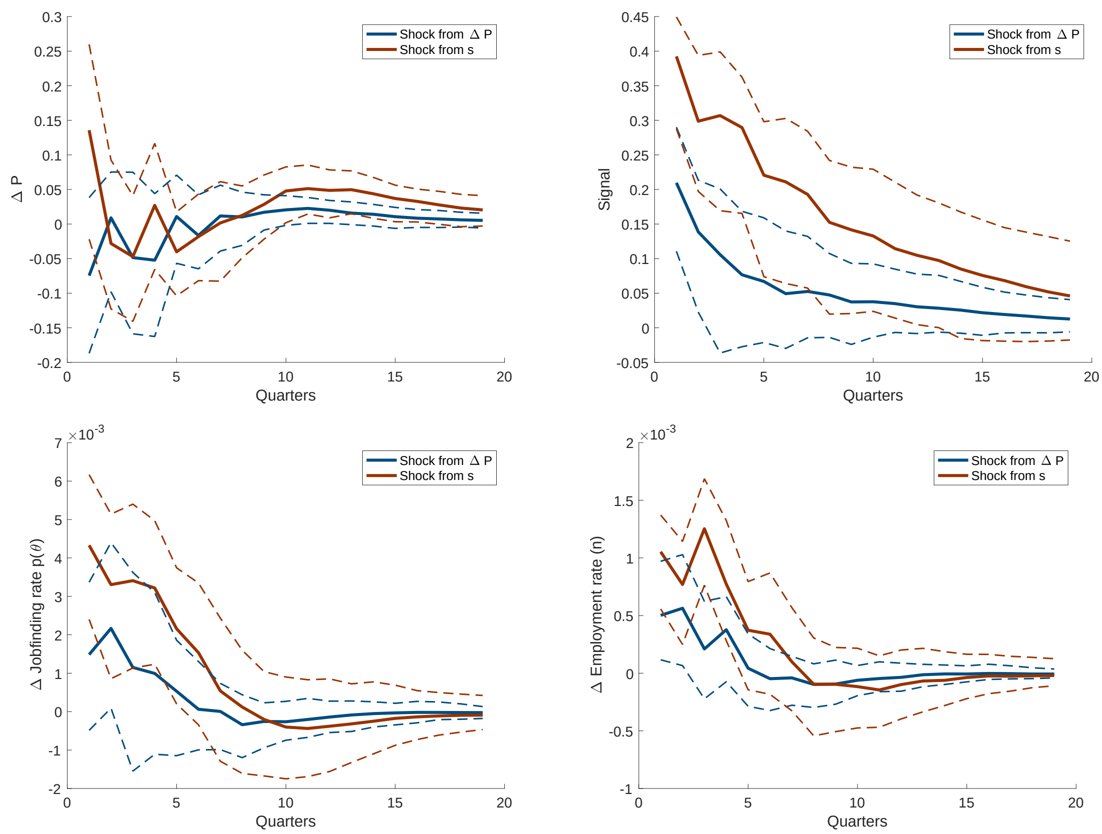


Figure 11: Impulse responses to one standard deviation shocks to productivity (blue) and the signal (red) from the quarter following the shock on the change in productivity, the signal, and the changes in the job finding and employment rate. Dashed lines show 95 % confidence intervals.

described by equation (39).

$$\begin{bmatrix} \epsilon_t \\ \nu_t \end{bmatrix} = \begin{bmatrix} b(L)\frac{\sigma_\nu}{\sigma_s} & -b(L)\frac{\sigma_e}{\sigma_s} \\ \frac{\sigma_e}{\sigma_s} & \frac{\sigma_\nu}{\sigma_s} \end{bmatrix} \begin{bmatrix} u_t \\ s_t \end{bmatrix} \tag{39}$$

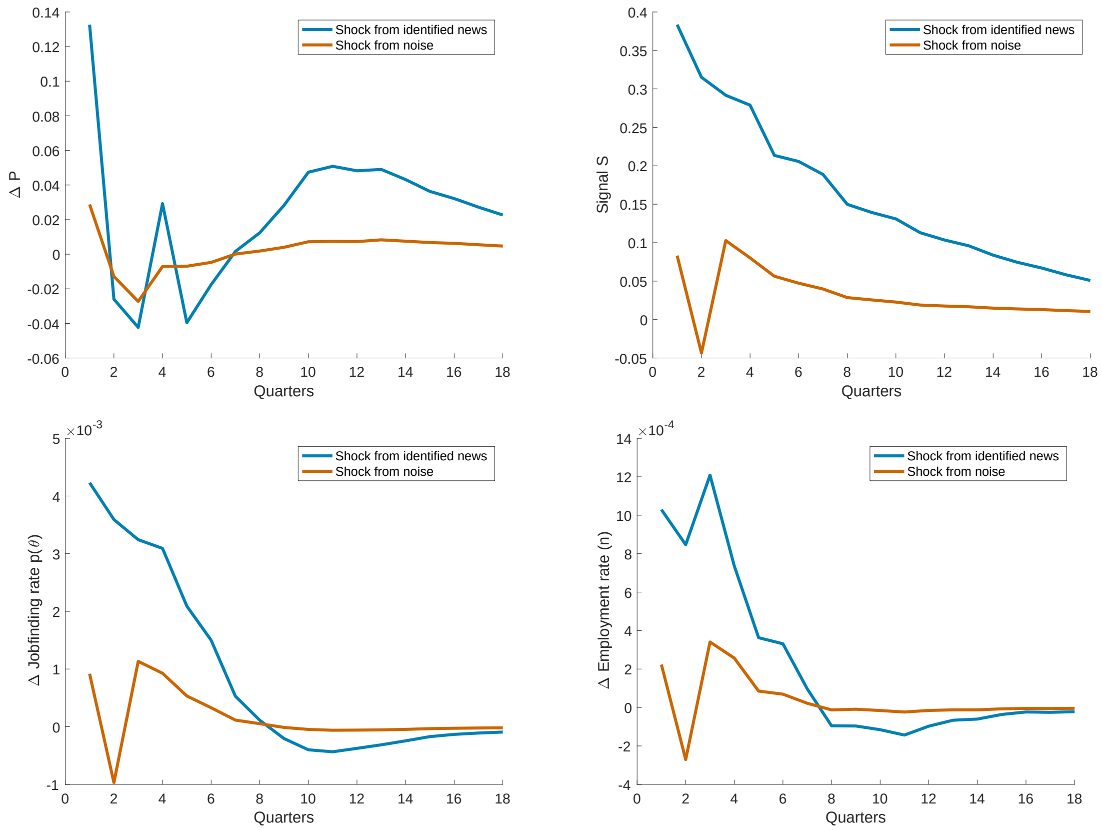
Here $b(L)$ is computed from the roots within the unit circle smaller than one in modulus of the polynomial estimate of the second column in the first row of $\tilde{A}$ described in detail (Forni et al., 2017). σ_s is the result of the volatility of the signal with $\sigma_s^2 = \sigma_\epsilon^2 + \sigma_\nu^2$. An estimation of $\frac{\sigma_\epsilon}{\sigma_s}$ and $\frac{\sigma_\nu}{\sigma_s}$ is achieved in the following way. As explained in (Forni et al., 2017) an estimate of $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu}$ can be gotten from dividing the estimated responses of the productivity series to surprise and signal shocks at the assumed lag length by each other. Thus $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = \tilde{B}_{1,2}/\hat{B}_{1,1}$, where $\tilde{B} = \tilde{A}_5$ to account for the four period lag between the signal and the quarter predicted and the subscripts of $tildeB$ capture the matrix elements. Due to the trigonometric relationship $\frac{\sigma_\epsilon^2}{\sigma_s^2} + \frac{\sigma_\nu^2}{\sigma_s^2} = 1$ The estimates for are then $\frac{\sigma_\epsilon}{\sigma_s} = sin(arctan(\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu}))$ and $\frac{\sigma_\nu}{\sigma_s} = cos(arctan(\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu}))$. The results in the current case are $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = 0.977$ and $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = 0.212$. Finally, (Forni et al., 2017) suggest to transform the fundamental representation to the structural representation by post-multiplying the moving average process in equation (38) with the matrix C in equation (40).

$$C = \begin{bmatrix} b(L)\frac{\sigma_\nu}{\sigma_s} & -b(L)\frac{\sigma_e}{\sigma_s} & 0 & 0 \\ \frac{\sigma_\epsilon}{\sigma_s} & \frac{\sigma_\nu}{\sigma_s} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{40}$$

The impulse response functions of the identified news and noise shocks are presented in Figure 12. The method is successful in limiting the response of output per worker to noise as can be seen from the first graph. Overall the response of the signal also matches the expected result from a news and noise shock, if there is a relatively small noise component. Of course, the brief negative dip of the signal to a noise shock is unexpected. A reason for this could be that the assumption that news and noise shocks are uncorrelated is too strong. Another problem could be that surprise shocks are mixed into the signal, and while the structural identification focuses on news and noise these could make the exact separation of the two more difficult. Nevertheless, both the job-finding rate and employment respond much stronger to the identified news than to the identified noise shocks.

The result of this empirical exercise suggests similarly to the DSGE model a limited importance of noise shocks on the labour market. A conditional variance decomposition of the forecast errors suggests that four quarters ahead the majority of fluctuations in the job-finding rate and the employment rate are caused by news rather than noise thereby confirming the results of the DSGE estimation that there is little noise driving the US labour market. The slightly stronger noise component in the variance decomposition in Table 7 may be due to the less precise separation of noise, news, and surprise shocks with the in-

Figure 12: Impulse responses to a 1% standard deviation shock ϵ_t (blue), v_t(black)



Series	*Quarters ahead*	1	2	3	4
Δ Job finding rate ($p(\theta)$)	Noise (ν)	4.49 %	6.79 %	10.87 %	8.24 %
	News (e)	95.51 %	93.21 %	89.13 %	91.76 %
Δ Employment rate (n)	Noise (ν)	4.49 %	9.29 %	7.36 %	10.85 %
	News (e)	95.51 %	90.71 %	92.64 %	89.15 %

Table 7: Variance decomposition of changes to the job-finding and employment rate due to identified noise to news.

struments at hand and the slightly different definitions of the shocks in the VAR compared to the DSGE model.

6 Interpretation of the result

This paper is as a first exploration into the question of whether agents' erroneous expectations over the expected surplus product of a job match are an important factor in changes in job creation on the aggregate. It finds in multiple setups that non-fundamental noise shocks play a very limited role in job creation, contrary to consumption and investment choices.

The robustness of the result is surprising and there are three interpretations possible regarding it.

- **Agents are well informed** about future labour productivity growth. This is the simplest explanation derived directly from the model. While there are surprises it may be that the reason agents on the aggregate seem better informed about job creation than consumption is that the decision-makers are different. A good part of labour market decision-making is done by firms who may be better informed about the productivity of jobs they open than consumers about their future incomes when making consumption and investment choices.

- **Self-fulfilling expectations** lead to expectations always matching labour productivity. In this case, the expectation of labour productivity rising or falling will lead to labour productivity fundamentally rising or falling. This is the case when there are strong aggregate complementarities of hiring, which for instance may be accompanied by increased demand or increased capital investment. Both may then lead to labour productivity moving in the direction of expectations in a quarter leading to no role in non-fundamental hiring movements and a quick aggregate reaction of hiring to labour productivity changes.

- **There is no forward-looking component in hiring decisions** due to very low hiring frictions or too high turnover. This explanation does not seem to be coherent with the data, given that even in the very conservative calibration used with low vacancy posting cost oriented on (Hagedorn and Manovskii, 2008) and a high exogenous separations noise can potentially play a significant role. However, from the different calibrations, it is clear that higher vacancy posting costs will lead to a higher role of noise, as will lower exogenous separations as both strengthen the importance of the forward-looking elements in the job-creation condition of the (Mortensen and Pissarides, 1994) random search model.

Of the three interpretations, the first and second are argued to be more likely, and the truth may be a combination of both. The results in this paper if either of these two interpretations is correct mean that variables capturing hiring behaviour are reliable indicators of agents expectations about fundamental labour productivity, and vice versa expectations are strong predictors of expected hiring activity. This robust result should be used to inform policy-making and merit continued high attention of central banks on labour market activity, possibly over investment or consumption activity when determining the state and future expectations for the economy.

7 Conclusion

This paper implements a DSGE model with information frictions and estimates the extent of noise agents face when making job creation decisions, which are based on their expectations about future aggregate labour productivity growth. Further, a strategy to identify noise in a VAR model is used for robustness to investigate the same question.

Both approaches find that noise is unlikely to play a significant role in employment and job creation in the United States labour market on the aggregate. Firms hiring decisions appear well informed about the present discounted value of a job match by observing current productivity, and signals on future innovations in aggregate worker productivity. Thus agents are able to separate permanent from temporary labour productivity shocks well. Variables capturing hiring behaviour, therefore, are found to be reliable indicators of agents expectations about fundamental labour productivity, and vice versa expectations are strong predictors of expected hiring activity.

This result is in accordance with investors and financial markets reacting strongly to surprises in the latest release of the employment report as shown in Figure 13. A recent empirical evaluation of this phenomenon can be found, for instance in (Bauer, 2014). The results of the paper also cast interesting questions on where the noise that has been found in aggregate consumption decisions by agents in (Blanchard and Quah, 1993) and (Forni et al., 2017) is mirrored on the supply side. If aggregate labour market decision-making is largely unaffected by noise around future productivity expectations, then noisy consumption choice regarding future productivity expectations is likely to be reflected in the capital input side of production. The results in this paper do not mean that there could not be information frictions regarding choices between idiosyncratic sectors or professions, or affecting decision-making in individual matches, but are for the behaviour of decision-making and job creation on the aggregate.[2] Overall, the robust result of this paper shows

[2]Information frictions between sectors and professions may be estimated with the extension to the DSGE

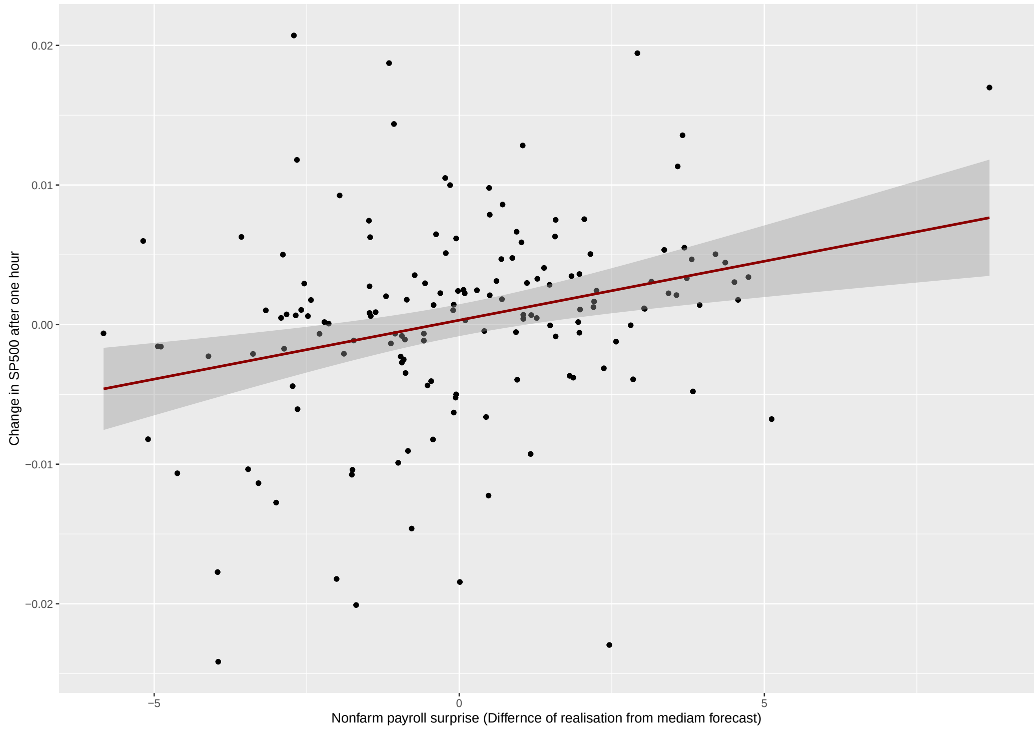


Figure 13: Effect of payroll surprises on the SP 500. The datasource is Bloomberg.

that aggregate variables capturing the choices taken on the labour market should be at the centre of attention of policymakers when determining the current state and future expectations for the economy.

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model proposed in Appendix D.

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Appendix A Model derivations

The agent Kalman filter

The agent Kalman filter is developed in the following way. Agents know that there is an unobserved process of the form in equation (41), but only observe only a_t and s_t which are however driven by the same shocks according to equation (42).

$$\begin{bmatrix} x_t \\ x_{t-1} \\ z_t \end{bmatrix} = \begin{bmatrix} 1+\rho^x & -\rho^x & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho^z \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} e_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{41}$$

$$\begin{bmatrix} a_t \\ s_t \end{bmatrix} = \begin{bmatrix} (1+\rho^x) & -\rho^x & \rho^z \\ (1+\rho^x) & -\rho^x & 0 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{42}$$

Finally, expectations on the permanent and temporary component of a_t have to add up to a_t and the signal is a combination of news and noise as shown in equation (43).

$$\begin{bmatrix} a_t \\ s_t \end{bmatrix} = D \begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} + \begin{bmatrix} 0 \\ \nu_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} + \begin{bmatrix} 0 \\ \nu_t \end{bmatrix} \tag{43}$$

Given these identities, the result is the agent Kalman filter is found in equation (44).

$$\begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} = \begin{bmatrix} 1+\rho^x & -\rho^x & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho^z \end{bmatrix} (I - KD) \begin{bmatrix} x_{t-1|t-1} \\ x_{t-2|t-1} \\ z_{t-1|t-1} \end{bmatrix} + K \begin{bmatrix} a_t \\ s_t \end{bmatrix} \tag{44}$$

Where I is the identity matrix, K is the converged Kalman gain and D a 2x3 matrix. Given that the covariance matrix of the shocks is positive semi-definite, as the three shocks e, η andν are independent with positive finite variance the Kalman gain will converge (Anderson, McGrattan, Hansen, and Sargent, 1996).

With equations (42), (43) , and (44) the expectations about future productivity growth can be described as the result of current expectations and the fundamental shocks e, η, and ν.

Linearising the dynamic equilibrium

Market clearing and the first order conditions require that the aggregate constraint of the economy is given by the consumption equation. Assume for simplicity $\alpha = 0$ and define $P = \frac{a_t}{\Pi_{s=1}^{L} a_{t-s}^{\gamma_s}}$.

$$c_t = a_t n_t - a_{t-L}(\kappa v_t - b(1 - n_t)) \tag{45}$$

$$\frac{\kappa}{q(\theta_t)} = \pi(E_t P_t - b) + \beta(1-\lambda)E_t[P_t \frac{c_{t+1}^{-\sigma}}{c_t^{-\sigma}}(\frac{\kappa}{q(\theta_{t+1})} - (1-\pi)\kappa\theta_{t+1})] \tag{46}$$

$$n_t = (1-\lambda)n_{t-1} + v_t q(\theta_t) \tag{47}$$

$$u_t = 1 - (1-\lambda)n_{t-1} \tag{48}$$

$$\theta_t = \frac{v_t}{u_t} \tag{49}$$

The steady-state value of a worker-firm relationship relative to the value of unemployment is $p = 1$. The steady-state of a is subject to change if the permanent component is shocked due to the unit root process. For the approximation here the steady-state of a is normalized at 1. Approximating the above equation at this steady-state with a first order log-linearisation yields:

$$\hat{c}_t = \frac{n}{c}[\hat{P}_t + \hat{n}_t] - \frac{\kappa v}{c}\hat{v}_t - \frac{bn}{c}\hat{n}_t + \hat{a}_{t-L} \tag{50}$$

$$\hat{\theta}_t = \psi_1 E_t \hat{P}_t + \psi_2 E_t \hat{\theta}_{t+1} + \psi_3(E_t \hat{c}_t - E_t \hat{c}_{t+1}) \tag{51}$$

With $\psi_1 = \frac{\pi m}{\kappa \xi \theta^{\xi}}$, $\psi_2 = \beta(1-\lambda)(1 - \frac{m(1-\pi)}{\xi}\theta^{1-\xi})$, and $\psi_3 = \sigma\beta(1-\lambda)\frac{(1-m(1-\pi)\theta^{1-\xi})}{\xi} = \sigma(\psi_2 + \beta(1-\lambda)\frac{1-\xi}{\xi})$

$$\hat{n}_t = (1-\lambda)\hat{n}_{t-1} + \lambda(\hat{v}_t - \xi\hat{\theta}_t) = \frac{(1-n)(1-\lambda)}{1-(1-\lambda)n}\hat{n}_{t-1} + \lambda(1-\xi)\hat{\theta}_t \tag{52}$$

$$\hat{u}_t = \frac{(1-\lambda)n}{1-(1-\lambda)n}\hat{n}_{t-1} \tag{53}$$

$$\hat{\theta}_t = \hat{v}_t - \hat{u}_t \tag{54}$$

If one assumes that $\sigma = 0$, thus that agents have a linear instant utility function it becomes straightforward to show that vacancy postings only depend on last period's employment and the expected productivity path.

$$\hat{\theta}_t = \psi_1 E_t \hat{P}_t + \psi_2 \psi_1 E_t \hat{P}_{t+1} + \psi_2^2 E_t \hat{\theta}_{t+2} = \psi_1 E_t \sum_{s=0}^{\infty} \psi_2^s \hat{P}_{t+s} \tag{55}$$

$$\hat{v}_t = \psi_1 E_t \sum_{s=0}^{\infty} \psi_2^s \hat{P}_{t+s} + \frac{(1-\lambda)n}{1-(1-\lambda)n} \hat{n}_{t-1} \tag{56}$$

This result is generalized to values of $\sigma \geq 0$ by inserting equation (50) and (52), and the resulting equations into (51) substituting out for $\hat{c}_t$, $\hat{c}_{t+1}.\hat{c}_{t+2}$,... . However, the resulting equation for $\hat{\theta}_t$ as a function n_{t-1} and past, current, and future values of a_t does not have a closed form representation.

Note that even if agents knew current period productivity, thus if a_t and p_t would be part of their information set in period t, hiring in the current period will still depend on the future productivity expectations $E_t p_{t+1}, E_t p_{t+2}, ...$ and would thereby still be affected by news and noise besides observed shocks to current productivity. To emphasize the potential effect of news and noise the arguably more realistic modelling choice has been made to exclude the precise value of current aggregate productivity from the agents' information set.

Appendix B Data description

The label of the series in question in the federal reserve database (FRED) is presented in square brackets during this section. **Worker Productivity (a)**
The product that a new worker-firm relation would create is the key driving factor in a search and matching model. This product p_t is assumed to depend in this model on the path of productivity a_t. The realized real output per worker could be used as a proxy for productivity a_t in this model as due to the modelling assumptions the marginal product of labour equals the current level of productivity.

This series would be ideal if real output Y_t is the product of $A_t N_t$, where $A_t = exp(a_t)$ and $N_t = n_t L_t$. L_t is the total labour force. In this case $log(\frac{Y_t}{N_t}) = a_t$. Looking at the data a_t is clearly an integrated process.

On the other hand, if the aggregate real output of the economy is actually better modeled by some Cobb-Douglas form $Y_t = A_t N_t^{1-\alpha} K_t^{\alpha}$ then the product contributed by taking on another average worker on a continuum of workers is $\frac{Y_t}{N_t} = A_t (\frac{K_t}{N_t})^{\alpha} = \tilde{A} N_t^{-\alpha}$. This explains the generalisation using $n^{1-\alpha}$ in the model. In this case movements in a capture both TFP and capital changes. K_t is some measure of productive capital and mpl_t is the marginal product of labour. Once one focuses on the changes over time $\frac{mpl_t}{mpl_{t-1}} = \frac{\frac{Y_t}{N_t}}{\frac{Y_{t-1}}{N_{t-1}}}$. Then $\Delta a_t + \Delta k_t = (log(\frac{Y_t}{N_t} - log(\frac{Y_{t-1}}{N_{t-1}}))$, where $k_t = \alpha log \frac{K_t}{N_t}$ is capital per active worker.

From the equation $\Delta log(\frac{Y_t}{N_t}) = \Delta a_t + \Delta k_t$ it is clear that under the alternative Cobb-Douglas assumptions for production, capital per employed worker not changing as a result of employment activity resulting from future expectation shifts is a critical assumption for the identification of productivity news and noise shocks when estimating the model parameters based on this series. This assumption holds if capital fully depreciates after the end of each period and capital input is chosen by firms once agents observe the productivity realization a_{t+1}. On the other hand, if these assumptions do not hold and capital per worker were to increase as a result of a positive expectation shift, then the productivity of hired workers would be, to some extent the result of a self-fulfilling prophecy. This would weaken the ability of the model to separate news from noise.

In the latter case, the amount of capital resources per worker going into production would correlate with noise and thus worker productivity would react and not stay flat in response to a noise shock. In this case, the identifying qualities of the series for separating productivity noise from news would be lost. The series then would only be useful in identifying noise in the labour market to the extent that this noise leads to hiring, but does not lead to marginal product of labour adjustments. Thus the series would be $\Delta log(\frac{Y_t}{N_t}) = \Delta a_t + \Delta k_t = \Delta \tilde{a}_t$ This would still be a useful estimation, but it is important to note the qualitative difference of noise in both cases. In the second case noise is the result of misinformation over the path of $\tilde{a}_t = a_t + k_t$, where k_t is a function of the expected path. It is still possible for agents to be misinformed about this path, but as the misinformation has an effect on k_t identification is weaker and limits the power of the estimation. This problem may be addressed in an extension of the model, which explicitly takes optimal choices of capital input into account.

One can test whether the random walk assumption of the model is plausible for the output per worker series a_t. This is done by testing the hypothesis that for the AR(1) process $\Delta a_t = \mu_a + \rho_a \Delta a_{t-1} + u_t$ the estimated coefficient $\hat{\rho}_a = 0$. An augmented Dickey-Fuller test reveals t-values of -10.739 and -10.075 for Δ *Output per worker based on the BLS index* and Δ *Real output per worker* respectively. This means that the random walk assumption for labour productivity a cannot be rejected. This confirms the assumptions taken in Section 3.1.

The productivity series on which the estimation is based is presented in Figure 14. This series is used in (Shimer, 2005). An alternative, yet very similar measure for output per worker is the series constructed by dividing real Output[GDPC1] by the number of workers Worker[PAYEMS]. This series is very similar as can be seen in Figure 15. Finally, (Forni et al., 2017) use potential output. Potential output per worker is significantly less volatile. The changes of the series can be seen in Figure 16. While it can be seen as a problematic series as it accounts for the economies employment potential as well the series provides a sense of the current marginal product of hiring a worker given that the economy is not at potential.

Job-finding rate ($p(\theta)$)

To find the job-finding rate I employ the procedure suggested in (Shimer, 2005). I update Shimer's estimation of the job-finding-rate and by also imposing the 10% correction for the presumed level shift of the short-term unemployed series from the beginning of 1994. This

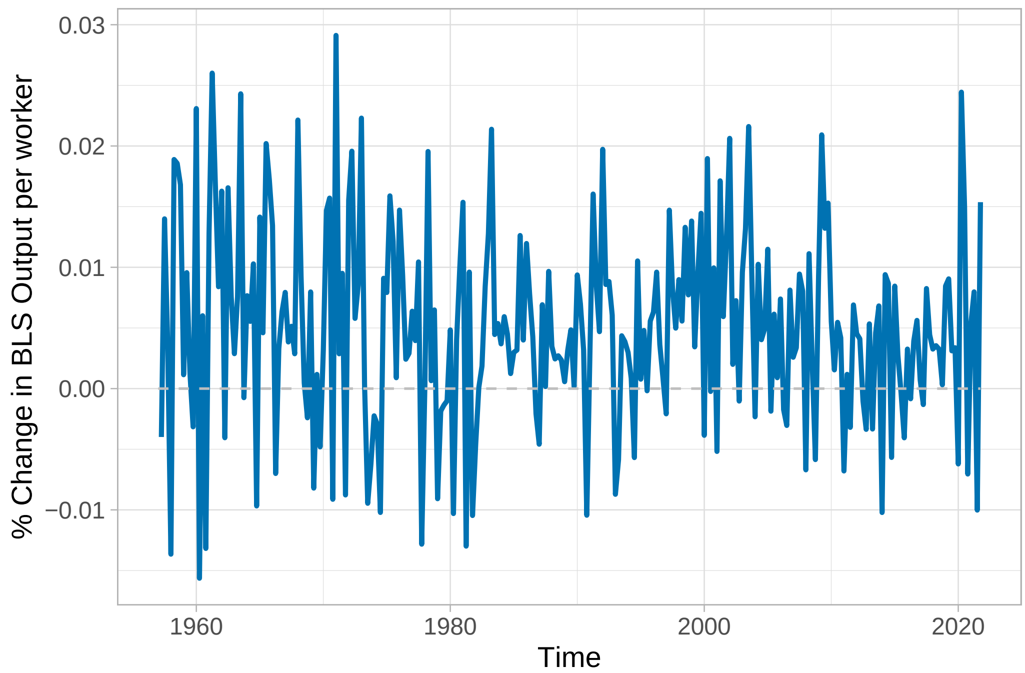

Figure 14: Changes in Labour productivity Δa_t based on Output per Worker [OPHNFB] computed by the bureau of labour statistics

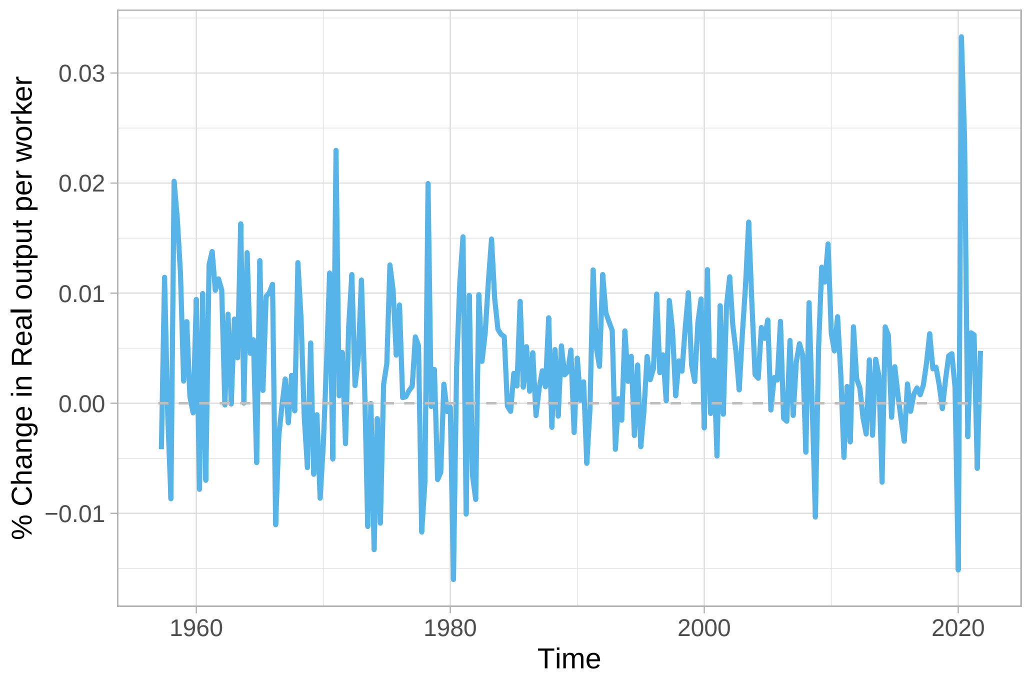

Figure 15: Changes in Labour productivity Δa_t based on Output[GDPC1] per Worker[PAYEMS]

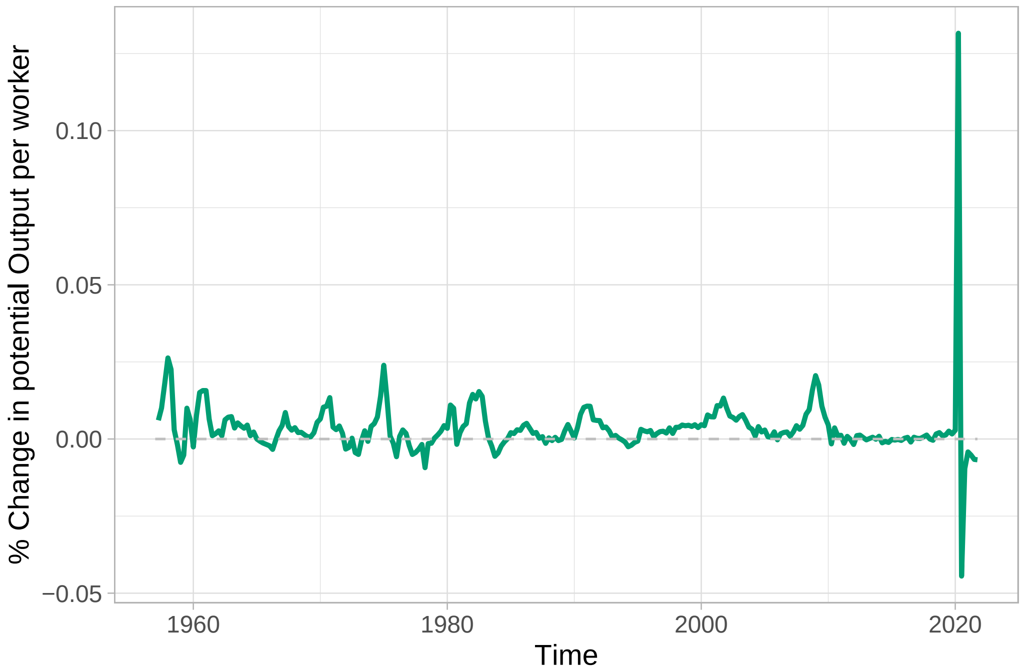

Figure 16: Changes in Labour productivity Δa_t based on potential Output[GDPPOT] per Worker[PAYEMS]

means estimating the job-finding rate by rewriting the law of motion of unemployment $U_t = U_{t-1} + S_t - f_t U_{t-1}$ to

$$f_t = 1 - \frac{U_t - S_t}{U_{t-1}}$$

, where S_t is the number of separated workers who didn't succeed to find a job in period t. The number of people unemployed less than a month acts as a proxy for S_t. The unemployment monthly unemployment level [UNEMPLOY] and the number of short-term unemployed [UEMPLT5] is retrieved from the FRED based on the data by the Bureau of Labour Statistics.

Admittedly, this estimation of the job-finding rate makes a lot of assumptions, that are not going to hold in reality. Among other things it presumes, similar to the model presented above, that long-term unemployed workers have the same probability in finding a job as recently unemployed workers. An assumption that is clearly rejected by empirical investigations. The monthly job-finding rate estimated by this procedure is plotted in Figure 17.

Due to a lack of data on monthly productivity for the sample these transition probabilities have to be transformed to quarterly transition probabilities. The transformation is done by calculating the probability of the worker of not finding a job in the past three months and subtracting this from 1. $p(\theta_t) = 1 - (1 - f_t)(1 - f_{t-1})(1 - f_{t-2})$

This series in Figure 18 seems to be downward trending. Such a negative trend in the job-finding rate could be explained by a negatively trending parameter of matching productivity. Matching productivity is assumed constant in the model. For this reason, the

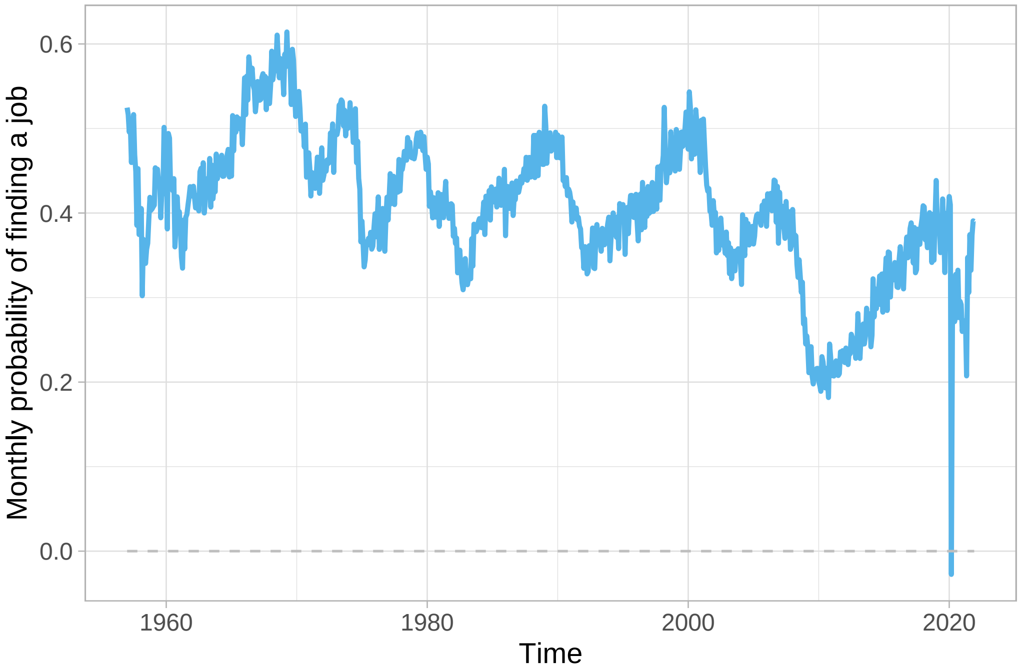

Figure 17: Monthly job-finding Rate f_t

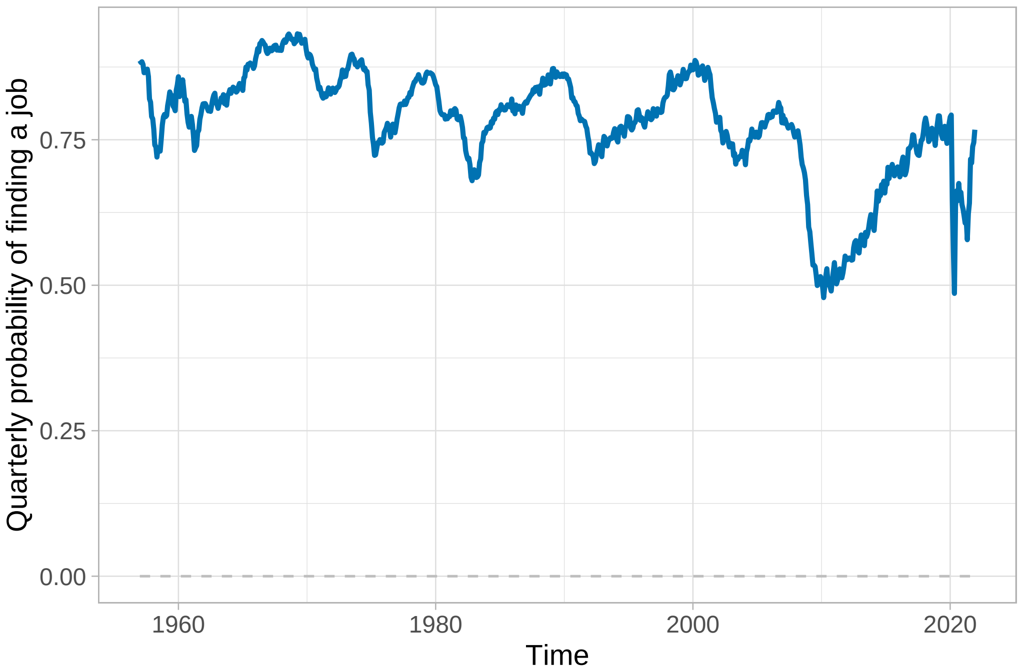

Figure 18: Quarterly job-finding Rate p(θ_t)

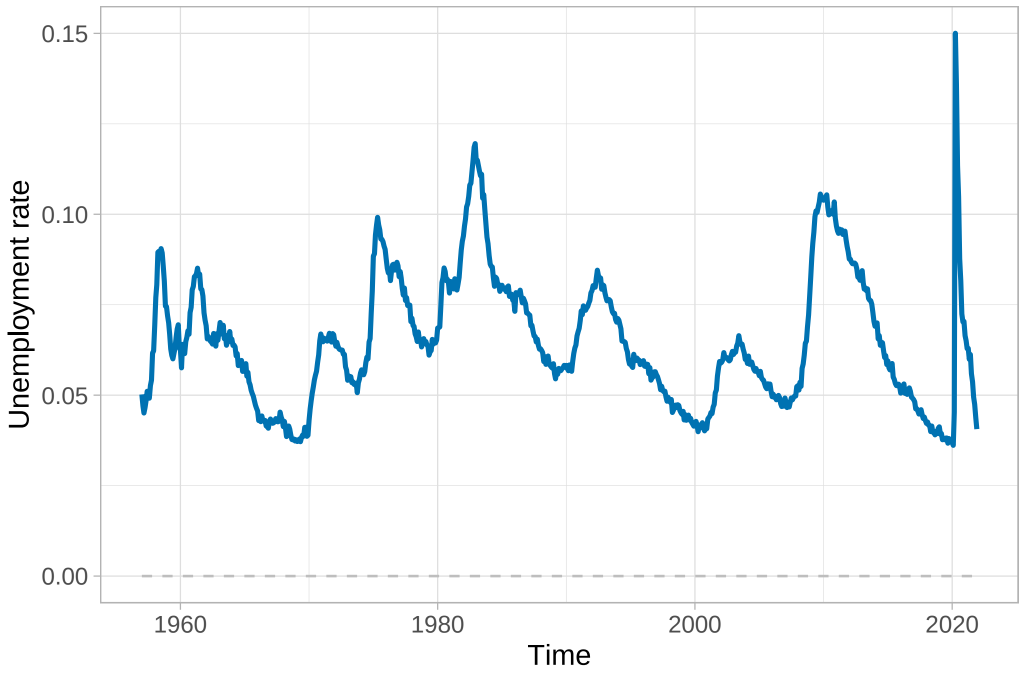

Figure 19: Unemployment rate.

model is estimated based on the demeaned changes in the job-finding rate, rather than the levels.

Unemployment ($1 - n_t$)

The unemployment series is based on the data available from the Bureau of Labour Statistics [UNEMPLOY/ (UNEMPLOY+PAYEMS)]. As for the job-finding rate, in order to avoid the estimation being influenced by not modelled trends, the estimation is based on the demeaned changes of the unemployment rate rather than the series levels.

Appendix C Additional simulation and estimation results

Simulation of the model in the FS implementation

Figure 20 shows the FS response of employment to the three type of shocks. In this case, an ϵ shock will lead to a permanent increase in the employment rate as the fundamental surplus of a match rises.

In the FS implementation, the impulse response function to a temporary shock is shown in Figure 21. Due to temporary productivity shocks being expected to have some persistence as given by ρ combined with the possibility that the increase in a_t was actually the result of an increase of the permanent productivity component, firms will increase hiring. The fact that a temporary increase also temporarily increases expectations in long-run a can be seen in Figure 4. The impulse responses are similar to the impulse response of a persistent technology shock in a conventional RBC model where the income effect outweighs the

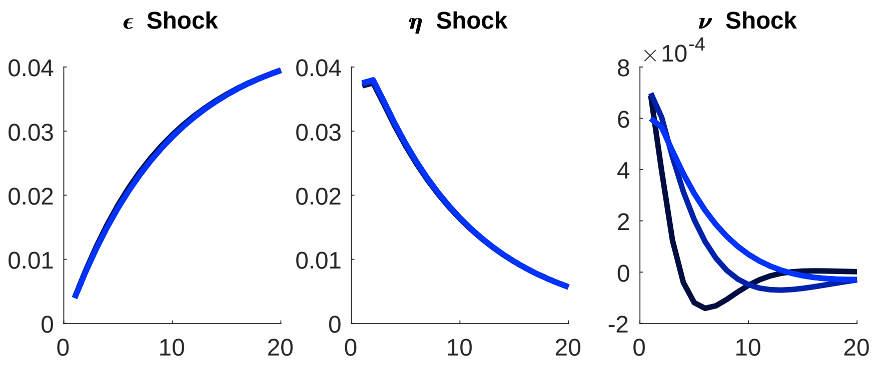

Figure 20: Comparison of a different strength of noise on the employment rate n with darker blue representing smaller noise for the FS implementation of the model.

Calibration	*Quarters*	1	2	3	4
	Fundamental surplus interpretation				
Baseline	Noise (ν)	3.18 %	0.47 %	0.08 %	0.01 %
	Permanent (e) %	96.82 %	99.53 %	99.92 %	99.99 %
Intermediate	Noise (ν)	5.1 %	0.79 %	0.14 %	0.02 %
	Permanent (e) %	94.9 %	99.21 %	99.86 %	99.98 %
Shimer	Noise (ν)	5.55 %	0.87 %	0.16 %	0.03 %
	Permanent (e) %	94.45 %	99.13 %	99.84 %	99.97 %

Table 8: Relative variance decomposition of noise and expected permanent labour productivity or fundamental surplus improvements with regard to the employment rate based on a simulation with a large noise impact

wealth effect leading to increased labour demand. Note that with higher noise it becomes harder and harder for firms to separate the temporary from the permanent increase, which would lead to both impulse responses becoming flatter.

Under the setup under the FS implementation in Table 8, where permanent shocks to labour productivity permanently increase the match surplus noise may still contribute up to 5.55 % of the short run variance in the employment rate,

Full variance decomposition

Table 9 shows the variance decomposition of all three shocks. Furthermore, simulations are shown for the case that agents have to predict labour productivity for the current period allowing noise to fully drive the short-run variance. In this now-casting scenario the job creation condition changes to equation (57).

$$\frac{\kappa}{q(\theta_t)} = E_t[\pi(P_t - b) + \beta(1-\lambda)P_{t-L+1}\frac{c_{t+1}^{-\zeta}}{c_t^{-\zeta}}(\frac{\kappa}{q(\theta_{t+1})} - (1-\pi)\kappa\theta_{t+1})] \tag{57}$$

Calibration	*Quarters*	1	2	3	4
	Fundamental surplus interpretation				
Baseline	Noise (ν)	1.56 %	0.37 %	0.07 %	0.01 %
	Temporary (η)	51 %	21.12 %	9.43 %	4.85 %
	Permanent (e)	47.45 %	78.51 %	90.5 %	95.14 %
Intermediate	Noise (ν)	2.54 %	0.62 %	0.13 %	0.02 %
	Temporary (η)	50.26 %	21.26 %	9.51 %	4.87 %
	Permanent (e)	47.2 %	78.11 %	90.36 %	95.11 %
Shimer	Noise (ν)	2.77 %	0.69 %	0.14 %	0.02 %
	Temporary (η) %	50.09 %	21.31 %	9.54 %	4.88 %
	Permanent (e)	47.14 %	78.01 %	90.32 %	95.1 %
	Match productivity interpretation				
Baseline	Noise (ν)	7.67 %	8.38 %	3.62 %	1.06 %
	Temporary (η)	46.84 %	0.05 %	1.69 %	1.99 %
	Permanent (e)	45.49 %	91.57 %	94.69 %	96.95 %
Intermediate	Noise (ν)	12.87 %	13.85 %	6.15 %	1.83 %
	Temporary (η)	43.65 %	0.01 %	1.73 %	2.16 %
	Permanent (e)	43.48 %	86.13 %	92.12 %	96.01 %
Shimer	Noise (ν)	13.95 %	14.99 %	6.71 %	2.01 %
	Temporary (η) %	43.01 %	0 %	1.72 %	2.19 %
	Permanent (e)	43.05 %	85.01 %	91.58 %	95.8 %
	Fundamental surplus interpretation, predicting $E_t(P_t)$				
Baseline	Noise (ν)	97.52 %	82.46 %	40.74 %	8.64 %
	Temporary (η)	0.35 %	0.39 %	0.28 %	0.12 %
	Permanent (e)	2.13 %	17.15 %	58.97 %	91.24 %
Intermediate	Noise (ν)	94.74 %	73.03 %	30.26 %	5.94 %
	Temporary (η)	1.34 %	1.55 %	1.17 %	0.59 %
	Permanent (e)	3.93 %	25.43 %	68.57 %	93.47 %
Shimer	Noise (ν)	92.44 %	66.73 %	25.04 %	4.74 %
	Temporary (η) %	2.26 %	2.53 %	1.81 %	0.92 %
	Permanent (e)	5.3 %	30.74 %	73.15 %	94.35 %
	Match productivity interpretation, predicting $E_t(P_t)$				
Baseline	Noise (ν)	99.57 %	96.56 %	82.25 %	38.46 %
	Temporary (η)	0.21 %	1.47 %	3.63 %	6.38 %
	Permanent (e)	0.22 %	1.97 %	14.12 %	55.16 %
Intermediate	Noise (ν)	99.53 %	96.2 %	81.51 %	38.62 %
	Temporary (η)	0.1 %	1.39 %	3.53 %	6.18 %
	Permanent (e)	0.38 %	2.41 %	14.96 %	55.2 %
Shimer	Noise (ν)	99.46 %	95.88 %	80.66 %	37.97 %
	Temporary (η) %	0.04 %	1.36 %	3.51 %	6.08 %
	Permanent (e)	0.5 %	2.77 %	15.83 %	55.95 %

Table 9: Relative variance decomposition of noise, expected temporary or permanent match productivity or fundamental surplus improvements with regard to the employment rate based on a simulation with a large noise impact

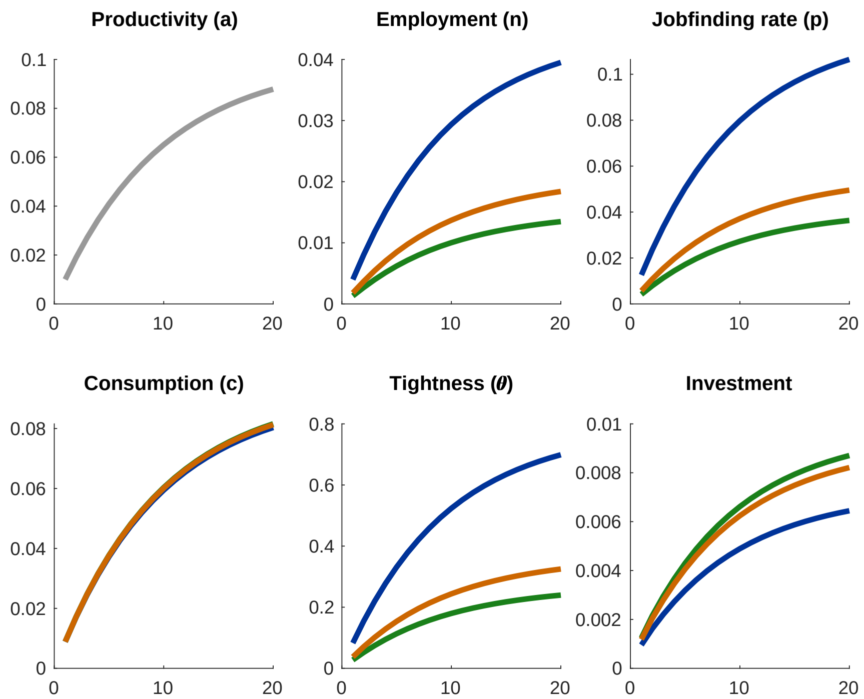

Figure 21: Responses to a shock to the permanent component (ϵ) in the FS implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

Table 10: Baseline estimated news and noise parameters by implementation with the series based on which the ML estimation was done in round brackets and the t-values in square brackets

Parameter estimated:	FS (Δa_t & Δu_t)	FS (Δa_t & $\Delta p(\theta_t)$)
ρ	0.8353 [75.9]	0.8453 [85.8]
σ_e	0.0666 [22.9]	0.0836 [2.5]
σ_ν	0.0065 [2.3204]	0.0134 [2.1]

Estimation results of the FS implementation of the model

Figure Figure 24 shows the estimated parameters for the FS implementation for estimations based on the unemployment and estimations based on the job finding series combined with productivity. Table 10 and Table 11 show the results of the maximum likelihood estimation and the relative variance decomposition for the FS implementation with the baseline calibration.

Appendix D Extension of the model

The model can be extended to study the noise in relative match productivity between sectors or professions. This can provide an estimation of the extent to which homogeneous workers are reluctant to switch sectors due to information frictions.

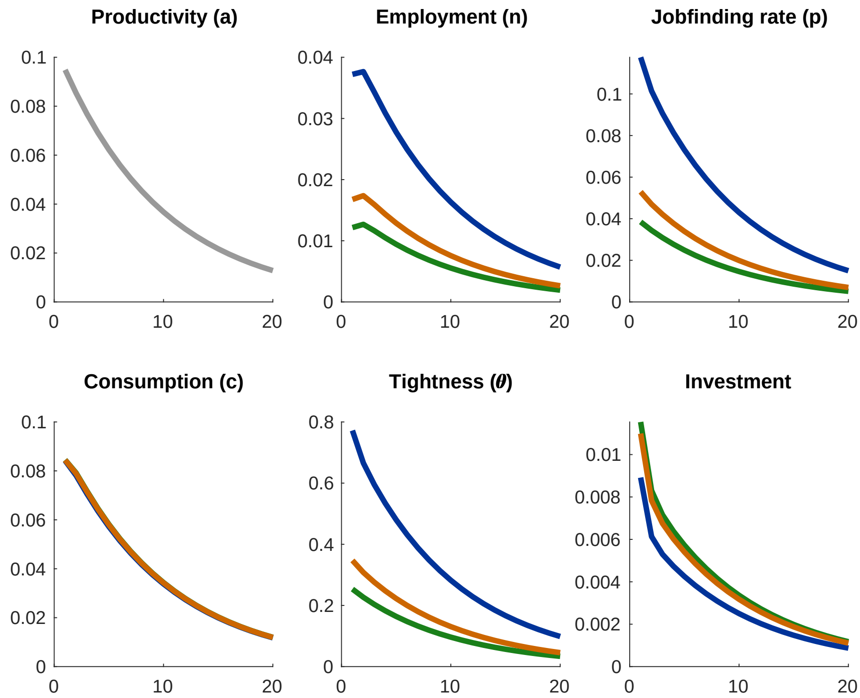

Figure 22: Responses to a shock to the temporary component (η) in the FS implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

Table 11: Estimation based of relative variance decomposition of noise and expected permanent labour productivity or fundamental surplus improvements with regard to the employment rate.

Calibration	*Quarters*	1	2	3	4
	Fundamental surplus interpretation				
Baseline	Noise (ν)	0.03 %	0 %	0 %	0 %
	Permanent (e) %	99.97 %	100 %	100 %	100 %

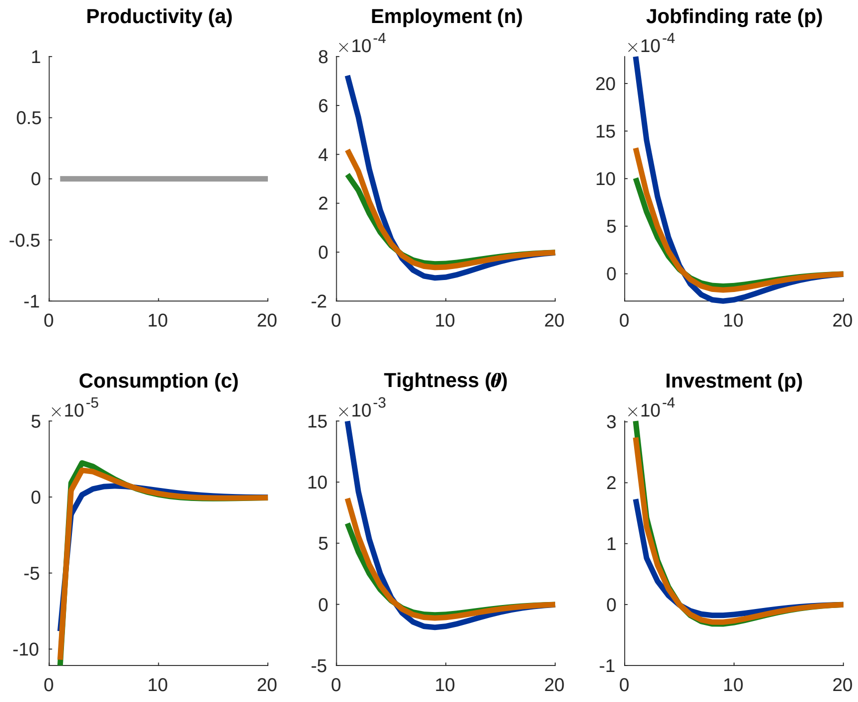

Figure 23: Responses to a shock to the noise shock (ν) in the FS implementation of the model. The baseline calibration is in blue, while the Shimer calibration is green, and the intermediate calibration is in orange.

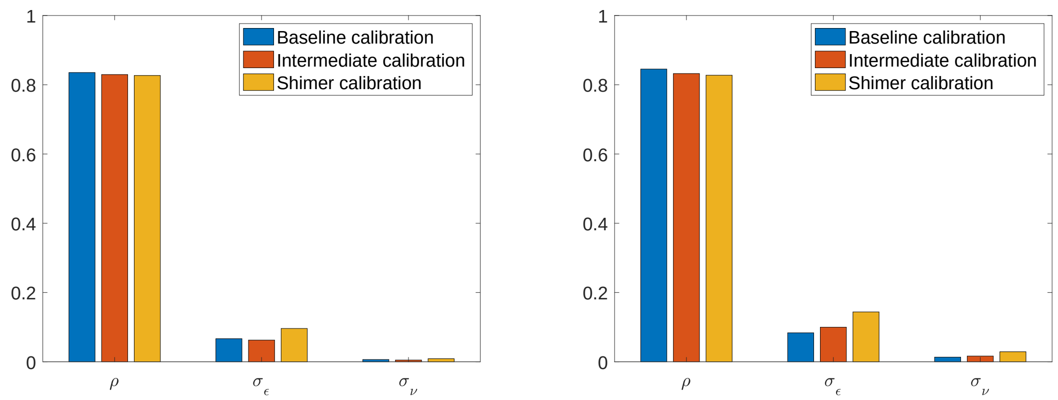

Figure 24: Results of the ML estimation of the model in the FS implementation. Estimation results based on the unemployment rate are on the left, while estimation based on the job-finding rate are on the right.

At the heart of these extensions is unemployed workers choosing to search in sector j such that their value of unemployment V^u is maximised as in equation (58).

$$V_t^u = b + p(\theta_t) \max_j [V_j^w - E_t(\mu_{t+t} V_{t+1}^u)] \tag{58}$$

In this case the relative output per worker is $\tilde{a}_{j,t} = \frac{a_{j,t}}{\bar{a}_t}$, where $\bar{a}_t = \sum_{j=1}^{J} n_{j,t}^{1-\alpha} a_{j,t}$ is the mean output per worker. The job creation condition for each sector is then a result of employment in the sector and expected labour productivity. Sectors with high employment will have high labour productivity. In equilibrium, the wages and match product of homogeneous workers will equalise. Shocks to relative productivity of one sector will lead to workers switching sectors. Large information frictions will delay the extent of these switches as workers will be afraid the increases in productivity could be temporary or non-fundamental.

$$\frac{\kappa}{q(\theta_{j,t})} = \int_{z_{s,t}}^{\bar{z}} [\pi(z_s \tilde{a}_{j,t} n_j^{-\alpha} - b) + \beta(1-\lambda) E_t[\frac{c_{t+1}^{-\zeta}}{c_t^{-\zeta}} (\frac{\kappa}{q(\theta_{j,t+1})} - (1-\pi)\kappa\theta_{j,t+1})]] h(z) dz \tag{59}$$

This setting will allow for a straightforward implementation via perturbation. Endogenous separation is introduced via idiosyncratic match productivity z_s in this setting to allow sectors to adjust and keep the match product in all sectors above the benefit from unemployment. Assuming a common information friction σ_ν sectoral wages, vacancies or hiring movements and output for homogeneous workers are sufficient to estimate the extent of information frictions. Homogeneity can be achieved by accounting for observable worker differences. The information frictions will introduce temporary mismatch driven by information frictions in the labour market as workers decide whether to switch industry or occupation, based on their expectation of an increase in match productivity in a sector being temporary or permanent.

Appendix E The model with endogenous job destruction

To extend the model with an exogenous job destruction element allow for the productivity of a job match to be subject to non-stochastic idiosyncratic productivity shocks drawn from a distribution $H(\zeta)$. These shocks are observed by the firm and worker at the beginning of the period, before production but after job creation, similar to (Den Haan et al., 2000). This will render the job creation condition changed to equation (60). Remaining exogenous job destruction is assumed to happen at the end of the period.

$$\frac{\kappa_t}{q(\theta_t)} = \int_{\tilde{\zeta}_t}^{\bar{\zeta}} \left[\zeta(1-\alpha) a_t n_t^{-\alpha} - w_t + \beta(1-\lambda) E_t[\frac{\mu_{t+1}}{\mu_t} \frac{\kappa_{t+1}}{q(\theta_{t+1})}] \right] h(\zeta) d\zeta \tag{60}$$

The left side of the equation still contains the cost of creating a job, while the right is the expected benefit to a firm from creating the job. $\bar{\zeta}$ is the upper most realisation of stochastic ζ, while $\tilde{\zeta}_t$ is the ζ realisation below which the firm and worker will decide to sever the match. This will be determined via the job destruction condition in equation (**??**), which can be found by substituting out for the wage in equation (61).

$$w_t = \pi b_t + (1-\pi)[\zeta(1-\alpha)a_t n_t^{-\alpha} + (1-\lambda)\frac{1}{r_t}E_t\kappa_{t+1}\theta_{t+1}] \tag{61}$$

$$\exp(\tilde{\zeta}_t) = \frac{1}{(1-\alpha)a_t n_t^{-\alpha}}\left[b_t - (1-\lambda)\frac{1}{r_t}E_t[\frac{\kappa_{t+1}}{q(\theta_{t+1})}) - (1-\pi)\kappa_{t+1}\theta_{t+1}]\right] \tag{62}$$

$$\exp(\tilde{\zeta}_t) = \frac{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}}{(1-\alpha)a_t n_t^{-\alpha}}\left[b - (1-\lambda)\frac{1}{r_t}(\frac{\prod_{s=1}^{L} a_{1+t-s}^{\gamma_s}}{\prod_{s=1}^{L} a_{t-s}^{\gamma_s}})E_t[\frac{\kappa}{q(\theta_{t+1})}) - (1-\pi)\kappa\theta_{t+1}\right] \tag{63}$$

Equation (64) shows the mean idiosyncratic labour productivity $\hat{\zeta}_t$ in a given period when H is log-normally distributed. ϕ and Φ here represent the pdf and cdf of the normal distribution.

$$\hat{\zeta}_t = \sigma_\zeta \frac{\phi((\tilde{\zeta}_t)/\sigma_\zeta)}{\Phi(-(\tilde{\zeta}_t)/\sigma_\zeta)} \tag{64}$$

The law of motion for employment is transformed to incorporate endogenous and exogenous job destruction as shown in equation (65).

$$n_t = (1-H(\tilde{\zeta}_t))[(1-\lambda)n_{t-1} + v_t q(\theta_t)] = (1-H(\tilde{\zeta}_t))[(1-\lambda)n_{t-1} + u_t p(\theta_t)] \tag{65}$$

Appendix F Dynare implementation for the DSGE model

Model file

The model file below implements an equilibrium where it is possible to switch between the fundamental and non-fundamental interpretations. The model file shows how alternative expected paths may be implemented in Dynare, which are separate from the actual productivity of the economy. It may be a useful guide for setting up a perturbed model with expectation driven decisions, where the expectations are different than the actual paths of the exogenous variables. The model is set up to compute the expected path of the future state n, x and z, and thereby determine the hiring decisions at present. Expectations of the converged Kalman filter are computed in the steady state file and passed as unchanging variables states K11 to K32 into the model file. In this way the estimation command is able to estimate these variables. The actual productivity path and signal will gradually lead to an update in expectations vie the Kalman gain variable K11 to K32.

```
close all;
%%%%%%%%%%%%%%%%%%%%%%%
% Dynare markup macro settings
%%%%%%%%%%%%%%%%%%%%%%

%Define approximation length into the future
@#define len = 20

%Set to 1 if ML estimation is desired
@#define est = 0

%Set to 1 if Fundamental interpretation
@#define fund = 0

%Define length of lag of ARMA for cost
@#define len_ar = 3

%%%%%%%%%%%%%%%%%%%%%%%
% Endogenous Variables
%%%%%%%%%%%%%%%%%%%%%%
var n, v, u, c, theta, Investment, wage, Output, a

@#for t in 1:len
n@{t} v@{t} u@{t} t@{t} a@{t} c@{t}
@#endfor

@#for i in 1:len+1
past_@{i}
@#endfor

aLR,
@#for i in 1:3
K@{i}1 K@{i}2
@#for j in 1:3
IKFA@{i}@{j}
@#endfor
@#endfor
Da,Dn, djf, du, Consumption dcons Unemployment Jobfindingrate
dx x z s prod dprod xtt xt1t ztt;

%%%%%%%%%%%%%%%%%%%%%%%
% Exogenous Variables
%%%%%%%%%%%%%%%%%%%%%%
varexo eta epsilon nu;

%%%%%%%%%%%%%%%%%%%%%%%
% Parameters
%%%%%%%%%%%%%%%%%%%%%%

parameters p_beta, sigma,lmb,xi,ppi,kap, b, m,
rho sig_u sig_nu exp_length p_alpha
@#for i in 1:len_ar+1
p_gamma_@{i}
@#endfor
;

load parameterfile;
set_param_value('m',pa.m);
set_param_value('p_beta',pa.beta);
set_param_value('sigma',pa.sigma);
set_param_value('lmb',pa.lambda);
set_param_value('xi',pa.xi);
set_param_value('ppi',pa.pi);
set_param_value('kap',pa.kappa);
set_param_value('b',pa.b);
set_param_value('sig_u',pa.sig_u);
set_param_value('rho',pa.rho);
set_param_value('sig_nu',pa.sig_nu);
set_param_value('p_alpha',pa.alpha);

exp_length = @{len};
@#if fund == 0
p_gamma_1 = 0 ;
p_gamma_2 = 0.6957742;
p_gamma_3 = 0.3042258;
p_gamma_4 = 0 ;
p_gamma_5 = 0;
p_gamma_6 = 0;
```

```
@#endif

% When all gamma are set to 0 no catchup processes influence the model
@#if fund == 1
p_gamma_1 = 0;
p_gamma_2 = 0;
p_gamma_3 = 0;
p_gamma_4 = 0;
p_gamma_5 = 0;
p_gamma_6 = 0;
@#endif

%%%%%%%%%%%%%%%%%%%%%%%
% Model
%%%%%%%%%%%%%%%%%%%%%%
model;

/*IKFA-- K-- are actually the values of the converged agent Kalman filter-
these are estimated in the steady state file from the parameters rho, sig_u, and sig_nu */
@#for i in 1:3
K@{i}1=K@{i}1(-1);
K@{i}2=K@{i}2(-1);
@#for j in 1:3
IKFA@{i}@{j} =IKFA@{i}@{j}(-1);
@#endfor
@#endfor

/*Productivity process*/
dx = rho*dx(-1) + (1-rho)*sig_u*epsilon;
dx = x - x(-1);
z = rho*z(-1) + (rho^0.5)*sig_u*eta;
prod = x + z;
dprod = prod - prod(-1);
dcons = c - c(-1);

/*Signal*/
s = x + sig_nu*nu;

/*Solving time t productivity expectation witht the agent Kalman filter values*/
xtt =    IKFA11*xtt(-1) + IKFA12*xt1t(-1) + IKFA13*ztt(-1) + K11*prod + K12*s;
xt1t =  IKFA21*xtt(-1) + IKFA22*xt1t(-1) + IKFA23*ztt(-1) + K21*prod + K22*s;
ztt =  IKFA31*xtt(-1) + IKFA32*xt1t(-1) + IKFA33*ztt(-1) + K31*prod + K32*s;

/******************************/
/*Actual model equations*/
/******************************/
n= (1-lmb)*n(-1)+m*v^(1-xi)*u^xi;
u=1-(1-lmb)*n(-1);
theta=v/u;
theta^xi*kap/m= ppi*(prod/past_1/n^p_alpha-b)+(1-lmb)*
p_beta*(c^sigma/ c1^sigma)*(a/prod)*(kap *t1^xi/m - (1-ppi) * kap*t1);
c= n*prod-kap*v+b*(1-n);
Investment=kap*v;
Consumption=n*prod -kap*v+b*(1-n);

/******************************/
/* This part is to to find the agents future expected path for the endogenous variables
based on the current expectations about the permanent and temporary component of productivity*/
/******************************/

/*Computing the expected productivity path based on the current expected values of productivity*/
a=xtt*(1+rho)-rho*xt1t+rho*ztt;
a1=(a-rho*ztt)*(1+rho)-rho*xtt+rho^2*ztt;
a2=(a1-rho^2*ztt)*(1+rho)-rho*(a-rho*ztt)+rho^3*ztt;
@#for t in 3:len
a@{t}=(a@{t-1}-rho^@{t}*ztt)*(1+rho)-rho*(a@{t-2}-rho^@{t-1}*ztt)+rho^@{t+1}*ztt;
@#endfor
aLR = xtt + (xtt-xt1t)*(rho/(1-rho));
Da=aLR-a@{len};

% Past labour productivity realisations
@#for t in 1:len+1
past_@{t}=  p_gamma_1 +
@#for j in 2:len_ar+1
@#if j== t+1
prod
@#endif
@#if j==t
a
@#endif
```

```
@#if j>t+1
prod(@{t-j+1})
@#endif
@#if j<t
a@{t-j}
@#endif
^p_gamma_@{j}*
@#endfor
1
;
@#endfor

/*Expected employment and pre-matching unemployment*/
n1= (1-lmb)*n+m*v1^(1-xi)*u1^xi;
u1=1-(1-lmb)*n;
@#for t in 2:len
n@{t}= (1-lmb)*n@{t-1}+m*v@{t}^(1-xi)*u@{t}^xi;
u@{t}=1-(1-lmb)*n@{t-1};
@#endfor

/*Expected theta and consumption*/
@#for t in 1:len
t@{t}=v@{t}/u@{t};
@#endfor

c1= n1* a -kap*v1+b*(1-n1);
@#for t in 2:len
c@{t}= n@{t}* a@{t} -kap*v@{t}+b*(1-n@{t});
@#endfor

/*Expected Job creation*/
@#for t in 1:len-1
t@{t}^xi*kap/m= ppi*(a@{t}/past_@{t+1}/n@{t}^p_alpha-b)+(1-lmb)*
p_beta*(c@{t}^sigma/ c@{t+1}^sigma)*(a@{t+1}/past_@{t})*(kap *t@{t+1}^xi/m - (1-ppi) * kap*t@{t+1});
@#endfor
t@{len}^xi*kap/m=
ppi*(a@{len}/past_@{len+1}/n@{len}^p_alpha-b)+(1-lmb)*
p_beta*(c@{len}^sigma/ c@{len}(+1)^sigma)*(a@{len}/past_@{len})*
(kap*t@{len}(+1)^xi/m - (1-ppi) * kap*t@{len}(+1));

/*Computing other variables of interest and integrating observation variables into the model*/
wage=b*ppi+(1-ppi)*(a+p_beta*(1-lmb)*c/c1*kap*t1);
Jobfindingrate=m*theta^(1-xi);
Unemployment=1-n;
Output= prod*n+b*(1-n);
Dn=n-n(-1);
djf=Jobfindingrate-Jobfindingrate(-1);
du=Unemployment-Unemployment(-1);
end;

steady;

shocks;
var eta; stderr 1;
var epsilon; stderr 1;
var nu;  stderr 1;
end;

model_diagnostics;
check;

stoch_simul(irf = 20, order =1, Periods=10000) Output Consumption
n Jobfindingrate  djf Dn Da a prod xtt aLR x Investment theta wage du;

/*Estimation part*/

@#if est == 1
estimated_params;
rho, 0.8,0,1;
sig_u, 0.006,0, 10;
sig_nu, 0.006,0, 10;
end;
varobs dprod djf;
estimation(datafile=Est_data1,prefilter=1,lik_init=2,first_obs=1);
shock_decomposition dprod djf;
@#endif
```

Steady state file

```
function [ys,params,check] = RS_steadystate(ys,exo,M_,options_)
% function [ys,params,check] = NK_baseline_steadystate(ys,exo,M_,options_)
% computes the steady state for the NK_baseline.mod and uses a numerical
% solver to do so
% Inputs:
%   - ys          [vector] vector of initial values for the steady state of
%                   the endogenous variables
%   - exo         [vector] vector of values for the exogenous variables
%   - M_          [structure] Dynare model structure
%   - options     [structure] Dynare options structure
%
% Output:
%   - ys          [vector] vector of steady state values for the the endogenous variables
%   - params      [vector] vector of parameter values
%   - check       [scalar] set to 0 if steady state computation worked and to
%                    1 of not (allows to impose restrictions on parameters)
% read out parameters to access them with their name
NumberOfParameters = M_.param_nbr;
for ii = 1:NumberOfParameters
  paramname = M_.param_names{ii};
  eval([ paramname ' = M_.params(' int2str(ii) ');']);
end
% initialize indicator
check = 0;
%% END OF THE FIRST MODEL INDEPENDENT BLOCK.
%% THIS BLOCK IS MODEL SPECIFIC.

%Finding the labour market steady state
load parameterfile;
y0=[2,0.5];
[y,fval]=fsolve(@(y) [ (ppi*(1/y(2)^pa.alpha- b)- kap /m *(1-p_beta*(1-lmb))* y(1)^xi)/(kap*p_beta*(1-lmb)*(1-ppi))-y(1)
      ,(m*y(1)^(1-xi))/(lmb+(1-lmb)*m*y(1)^(1-xi))-y(2)],y0);
theta=y(1);
n=y(2);
u=1-(1-lmb)*n;
v=theta*u;
c= n -kap*v+b*(1-n);
Investment=kap*v;
Unemployment=1-n;
Output=n+b*Unemployment;
Jobfindingrate=m*theta^(1-xi);

%Setting the productivity processes steady state
z=0;x=1;dx=0;s=1;
prod=1;
dprod=0;
a=1; aLR=1; Da =0;
xtt=1; xt1t=1; ztt=0;

%Steady states of the agent's expected path of the endogenous variables
for i = 1:exp_length+10
    eval(sprintf('c%d= %s',i,'c;'));
    eval(sprintf('n%d= %s',i,'n;'));
    eval(sprintf('v%d= %s',i,'v;'));
    eval(sprintf('u%d= %s',i,'u;'));
    eval(sprintf('a%d= %s',i,'a;'));
    eval(sprintf('t%d= %s',i,'theta;'));
    eval(sprintf('past_%d= %s',i,'1;'));
end

%Steady states for other variables of interest
wage=b*ppi+(1-ppi)*(a+p_beta*(1-lmb)*c/c1*kap*t1); Consumption=c; Dn=0; du=0; djf=0; dcons=0; DUnemployment=0; DLYpN=0;
      DLYPotpL=0; DConsumption=0;

% Agent Kalman filter
A = [ 1+rho -rho 0 ; 1 0 0 ; 0 0 rho ];
B = [ (1-rho)*sig_u 0 0 ; 0 0 0 ; 0 0 (rho^.5)*sig_u ];
S_U = [ 1 0 0 ; 0 0 0 ; 0 0 1 ];
F = [ 1 0 1 ; 1 0 0 ];
G = [0 0; 0 sig_nu ];
S_V = [0 0; 0 1 ];
Ome = eye(3,3);
for iter = 1:1000;
    K = Ome*F'*inv(F*Ome*F'+G*S_V*G');
    Ome = A*(Ome-K*F*Ome)*A' + B*S_U*B';
end;
IKFA = (eye(3,3) - K*F)*A;
```

```
%Converged Kalman filter results
IKFA11= IKFA(1,1); IKFA12= IKFA(1,2); IKFA13= IKFA(1,3); IKFA21= IKFA(2,1); IKFA22= IKFA(2,2); IKFA23= IKFA(2,3); IKFA31
      = IKFA(3,1); IKFA32= IKFA(3,2); IKFA33= IKFA(3,3);
K11= K(1,1); K12= K(1,2); K21= K(2,1); K22= K(2,2); K31= K(3,1); K32= K(3,2);

%% END MODEL SPECIFIC BLOCK
params=NaN(NumberOfParameters,1);
for iter = 1:length(M_.params) %update parameters set in the file
  eval([ 'params(' num2str(iter) ') = ' M_.param_names{iter} ';' ])
end

NumberOfEndogenousVariables = M_.orig_endo_nbr; %auxiliary variables are set automatically
for ii = 1:NumberOfEndogenousVariables
  varname = M_.endo_names{ii};
  eval(['ys(' int2str(ii) ') = ' varname ';']);
end
```