# Is Noise Driving Job Creation?




Philip Schnattinger
St Antony's College
University of Oxford

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**Abstract**

This paper studies the effect of noise on the expected value of a firm-worker match in the labour market. In the data, such noise shocks would look like spontaneous increases in labour demand, which cannot rationally be justified by the current and future productivity of the employed worker. A significant amount of noise in the labour market would prevent the correct identification of the response of labour market variables with respect to news shocks. The paper applies the empirical approaches in Blanchard et. al. (2013) and Forni et. al. (2017) to the labour market to estimate the extent to which aggregate job creation is driven by noise rather than news. Based on the estimation of the DSGE model and the structural VAR model using US data, the paper finds that it is unlikely that noise shocks play a significant role in hiring and job creation, as on the aggregate level firms generally anticipate the future output produced by newly hired workers correctly.

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# Is Noise Driving Job Creation?

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## 1 Introduction

A feature of job creation that is rarely modelled in real business cycle models is that the decision of a firm on whether to employ a worker has a substantial forward looking component. When hiring a new worker, the firm's management will be concerned about the current and the future value that the new hire would bring to the firm. This value will usually have to outweigh the costs that come with hiring, training, paying, and integrating the new worker in 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 his time to other productive activities.

These decision making processes are at the heart of the Mortensen-Pissarides search and matching model (Mortensen and Pissarides 1994, Pissarides 2000), where they are captured by 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 Theodoridis and Zanetti 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 2.1 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.

Recently, a number of empirical findings have suggested that a substantial part of the movements in aggregate consumption are caused by noise shocks rather than news shocks (Blanchard et. al. 2013, Forni et. al. 2014 and 2017) . These noise shocks could be considered wrong news, which lead agents to erroneously adjust their expectations over future productivity. As both the aggregate consumption choice and aggregate job creation depend to an extent on the anticipated state of future economic fundamentals, these findings raise the question whether some fluctuations in the labour market could also be attributed to noise rather than news. Such noise shocks would look in the data like spontaneous increases in labour demand, which cannot be justified by the current and future productivity of the employed worker. A significant amount of noise in the labour market would prevent the correct identification of the response of labour market variables with respect to news shocks. This paper applies the empirical approaches in Blanchard et. al. (2013) and Forni et. al. (2017) to the labour market to estimate the extent to which aggregate job creation is driven by noise rather than news. In other words, the empirical question in this paper is: Disregarding surprise productivity shocks, how precise are agents' expectations about the aggregate value that an employment relationship will provide?

For the purpose of answering this question, a simple DSGE model is developed in which variations in job creation, and thereby employment and the number of open vacancies, depend on news or noise. This is achieved by combining a framework in which agents receive noisy information over future productivity growth as developed in Lorenzoni (2009 and 2011), with a search and matching model of the labour market. The intuition of this model is the following. Agents receive a noisy signal providing them with information about future labour productivity growth. As

there are labour market frictions, firms take a forward looking approach to hiring. The signal provides firms with information about the expected 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 labour productivity growth is 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. If we assume that the econometrician, as an outside observer, has information about both the actual productivity and the labour market realizations, as well as the optimal response of firms and workers given their productivity expectations, then the observer can gain information about the nature of the signal driving expectations without the need to observe it. If the behaviour of agents anticipates future movements in the productivity process accurately and speedily then the signal is probably not very noisy, while if the behaviour of agents leads to fluctuations in labour market outcomes without movements in the productivity series then noise would be identified as being an important driver of the labour market on the aggregate level. In this environment it is also possible to simulate the maximum impact noise could have on the labour market given the calibration assumptions. The potential maximum impact is achieved when the signal is equally informative and noisy, thus when the variance of the noise and the productivity shock are equal.

The simulated model shows then that there exist calibrations consistent with US employment fluctuations, where about 10% of the forecast error variance in the employment rate one quarter ahead is caused by noise. This is certainly a large amount, but it would not be enough to explain, for instance the Shimer puzzle, thus the missing volatility in job creation, which cannot be explained by productivity movements (Shimer 2005). Bringing the model to the data and estimating the parameters of the news and noise process by maximizing their likelihood follow-

ing the empirical strategy suggested in Blanchard, l'Huillier, and Lorenzoni (2013), suggests that the volatility of the noise shock is insignificantly small, and that noise plays no role in aggregate job creation. 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 which 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 autoregressive 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, around 90 % of the forecast error variance in the job-finding rate and 95 % in the employment rate in the first two quarters are found to be caused by news, while only 10% and 5% respectively are due to noise confirming the results of the DSGE model.

To the author's knowledge, this paper is the first to study the potential effect of noise shocks on the labour market. Its contribution lies in suggesting two avenues to address this question by adapting models developed for estimating the extent to which consumption is driven by noise and applying these to the US labour market. Based on the estimation of the DSGE model and the structural VAR model, the paper finds that it is unlikely that noise shocks play a significant role in hiring and job creation, as on the aggregate level firms generally anticipate the future output

produced by newly hired workers correctly. The paper thereby makes an empirical contribution by providing an answer to the question of whether noise plays a role in the job creation in the US labour market and showing that noise is not likely to be a promising avenue for explaining the Shimer puzzle. This result indicates that the approach taken by Venkateswaran (2014), which aims to explain the Shimer puzzle by shifting the informational problem for the firm management from separating aggregate news and noise to separating firm idiosyncratic from aggregate productivity shocks, may hold more promise for explaining the additional volatility in job creation.

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 simple search and matching model for estimating the news and noise components in the labour market is presented. In the third part the mechanisms illustrated in the second part are applied to the data and the distribution of news and noise shocks are estimated with a maximum likelihood approach, while the fourth part compares the results of the third part to the results of a vector autoregression 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 limitations of the analysis and suggests further extensions to address the limitations. Section six concludes and relates the findings for the labour market to the findings for aggregate consumption.

# 2 Literature review

## 2.1 News driving business cycles

The renewed interest of macroeconomists in news shocks can be traced back to Beaudry and Portier's seminal 2004 and 2006 papers (Beaudry and Portier 2004 and 2006).

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). This definition of a Pigou cycle is henceforth used in this thesis. In the model proposed in the 2004 paper, agents are subject to two kinds of exogenous shocks. The first shock is an information shock received at time t, about productivity growth n periods in the future, while the second shock is the actual growth realization at time t+n. In the present day literature, these two shocks are more commonly referred to as news and surprise shocks. These shocks are then embedded in a three-sector model with capital adjustment costs. The three sectors are consumption goods, non-durable goods, and durable goods. The durable and non-durable goods are complementary inputs in producing the final consumption goods. Only labour is used as an input in producing non-durable goods, and for investing in the durable goods. Only the technological process of producing the non-durable goods is subject to stochastic shocks. The durable goods sector grows continuously according to a trend. The model then produces Pigou cycles when agents expect a higher growth in the future productivity of the non-durable goods input in the production of consumption goods. This will mean that the economy needs to build up durable goods faster to optimally produce consumption goods, leading to an expansion of investment, employment, aggregate output, and consumption. Consumption rises as well as the number of hours worked increases in order to produce the non-durable goods, and as the amount of non-durables increases, the amount of consumption goods produced also rises. The results of their matching moment exercise of this model on US data suggest that agents receive correct news shocks 82 % of the time, and are surprised by actual growth 18 % of the time.

In their 2006 paper, Beaudry and Portier show that the data supports the existence

of Pigou cycles. Using stock market prices as an identifier for expected long-run productivity growth in a VAR model, the paper found that innovations in these expectations and future actual growth are highly correlated. This is achieved by orthogonalizing innovations in the stock market, which are not due to contemporary productivity changes, and thus must be driven by expectations, and innovations in current total factor productivity. The finding of the paper runs counter to what a conventional RBC model would suggest. In conventional RBC models business cycle fluctuations are the result of surprise innovations in productivity. The VAR suggests, however, that in most cases agents are actually not surprised by changes in productivity, as they have previously received news on these productivity changes, leading expectations and therefore the prices in the stock market to change. Thus, the paper suggests that the main drivers of business cycles are actually news shocks, and not surprise shocks.

This empirical finding led to the search of theoretical models that could actually produce Pigou cycles in response to news shocks. As shown in Beaudry and Portier (2007), a plain one sector RBC model with perfectly competitive markets and constant returns to scale production technology cannot produce a positively correlated co-movement of consumption, employment, and investment, i.e. a Pigou cycle. Intuitively, the reason for this is that consumption and investment can only rise in response to an expectation shock if labour input were to rise as well. However, in a plain one sector RBC model labour demand won't rise as long as productivity stays the same. Labour supply may rise, but leisure and consumption are normal goods and therefore giving up on leisure today to enable higher consumption in the form of investment in capital for consuming tomorrow would naturally also require giving up consumption. Therefore the positive co-movement of employment, labour output, and consumption, which is necessary for a Pigou cycle, is impossible.

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. The instantaneous

utility function proposed is $\frac{(C_t - \psi N_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma}$ with $X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}$. This specification induces internal habits in the agents, which allow for controlling for the wealth effect of a news shock on labour supply. Investment adjustment costs will provide and incentive to smooth investment and thus react to a positive news shock by increasing investment in the present. This increased investment will lead to a fall in the cost of capital utilization, leading to increased capital utilization. Increased capital utilization raises the product of labour, thus as long as the wealth effect is small enough, labour input will rise. Thereby these three elements together produce a Pigou cycle. Jaimovich and Rebelo then include labour adjustment costs in the model and find that these help 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 stronger 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 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.

Theodoridis and Zanetti (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.

Barsky and Sims (2011) use a structural VAR approach to identify news shocks. The authors define the news shock as a shock that is uncorrelated to current total factor productivity (TFP) innovations and displays the highest correlation with future TFP developments. Contrary to the previous findings, this identification strategy suggests that consumption rises in response to a positive news shock, but output, employment, and investment decrease. These results would support the traditional RBC view. However, the identification strategy is questionable as there is no real reason why the news shock should be uncorrelated with the present TFP innovation. It might be that a large part of their identified news shocks are actually noise shocks, thus shocks where the agents are actually misinformed about future TFP.

Schmitt-Grohé and Uribe (2012) employ maximum likelihood and Bayesian techniques to estimate a fully specified DSGE model and identify news and surprise shocks. The authors argue that the aforementioned structural VAR models may not identify structural shocks correctly due to invertibility issues and the tendency of the models to focus on identifying only news shocks to one measure of productivity (usually TFP or investment specific shocks). Building on the results of Jaimovich and Rebelo (2009), they enrich the RBC model with real rigidities. Con-

cretely they introduce variable capital utilization, investment adjustment costs, and imperfect competition in the labour market. Additionally, they introduce internal consumption habit formation to control for the wealth elasticity of labour supply as described above. The model has seven stationary and non-stationary shocks inspired by Smets and Wouters (2007). The non-stationary series are detrended for estimation purposes by dividing the paths of the variables that depend on integrated shocks through the lagged shock, and thus basing the estimation on the growth rate of the endogenous variable, rather than its level. Using this framework, the authors find that about half of the variance of output, consumption, labour input, and investment are explained by anticipated (news) shocks. Interestingly, Schitt-Grohé and Uribe find that wage mark-up shocks, government spending, and investment specific shocks account for the majority of fluctuations in output due to anticipated shocks, while they find that TFP shocks are largely unanticipated by agents.

Forni, Gambetti, and Sala (2014) employ a factor-augmented VAR (FAVAR) model to test the fundamentalness of the Beaudry and Portier (2006) representation and other VAR models estimating the effect of news shocks. Using the orthogonality test proposed in Forni and Gambetti (2014) the paper finds that only the representation in Barsky and Sims (2011) is fundamental. The paper's name "no news in business cycles" could be considered as overly dramatic. Using their identification strategy, which involves finding principal components to different VAR specifications and defining the news shock to be the shock that best anticipates TFP in the long-run and does not move on impact, the authors in fact find that 20% of the volatility of output at business cycle frequencies is caused by news shocks. However, the impulse responses to the identified news shocks do not display a Pigou cycle as consumption falls in response to positive news. Given the similarity to the Barsky and Sims (2011) approach the same doubts about the identification strategy as formulated above apply, and it may be that part of the identified news shocks are actually noise shocks, which could limit the ability to of the model to recover correct impulse responses.

## 2.2 Is all "news" news?

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 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 2011) develops a setup for the productivity process that can be used for estimating the importance of noise shocks in business cycle fluctua-

tions. 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, l'Huillier, and Lorenzoni (2013) and in the model in this paper (see section 3.1). Blanchard, l'Huillier, and Lorenzoni (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.

Barsky and Sims (2012) assume that signals on future productivity are at least to some extent observable in the forward looking questions of the Michigan survey on consumer confidence. Using a combination of VAR and DSGE modeling the authors attempt to test the importance of animal spirits, which they interpret as noise in the consumer confidence data leading to effects on economic activity, against the view that expectation shifts summarize news about future fundamentals. First the authors show with a vector autoregression that there is indeed information on future productivity in consumer confidence data. In a next step they proceed to estimate the parameters and impulse responses to noise and news shocks. The measure of noise in Barsky and Sims (2012) is made up of two shocks. While they define one shock as measurement error in the confidence data, they conclude that the other shock are the animal spirits. Taking both of these noise shocks together

they account for about half the variation in the expectation data. The authors find that the animal spirits shock has a limited effect on consumption and income. The authors conclude that there are mostly news shocks about future productivity in the consumer confidence data and that the animal spirits effects are very weak.

Forni, Gambetti, Lippi, and Sala (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. 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 datapoints. 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.

## 2.3 Placement of this paper in the literature

This paper 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 aforementioned empirical results, it is taken as given that hiring in labour market dynamics depends largely on anticipations about the future productivity of the hired workers. The techniques from the literature studying the effect of noise shocks on consumption and output are then adapted and applied to the labour

market to model and estimate the extent to which shifts in anticipations about the future productivity of the hired workers are caused by noise shocks.

# 3 A model of the labour market where job creation is driven by news and noise

## 3.1 Labour productivity

In order to formulate a model for estimating the effects of news and noise on the labour market, the same assumptions on the processes contributing to the product of labour as in Blanchard, l'Hullier, and Lorenzoni (2013) are made. The observed process $a_t$ is the product of an employed worker in the past period (t-1) and is assumed to consist of a unobserved permanent and a temporary component:

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

The difference of the permanent component, and the temporary component are assumed to be stationary processes. The process x can be viewed as capturing permanent improvements in the production technology, while z captures short-term productivity gains.

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

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

Agents neither observe the permanent nor temporary component of the process $a_t$, nor its next realization at the end of period t $a_{t+1}$. Thus concerning the process $a$ only the past realizations $a_t, a_{t-1}, a_{t-2}, ...$ are part of the agents' information set in period t. Additionally, all agents in the economy receive a noisy signal over the

share of permanent productivity in past productivity of the form:

$$s_t = x_t + \nu_t \tag{4}$$

The productivity shocks $e, \eta$ and the noise shock $\nu$ are assumed to be independently, identically, and normally distributed with mean 0 and variance $\sigma_e^2, \sigma_\eta^2$, and $\sigma_\nu^2$.

Furthermore, the simplifying assumption is made that no information over the magnitude or direction of future productivity is contained in the productivity process $a$ itself and all information that exists about future productivity developments is contained in the signal. For this purpose 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 (see Lorenzoni 2011, and Blanchard, l'Hullier, and Lorenzoni 2013):

$$\rho^x = \rho^z = \rho \tag{5}$$

$$\rho\sigma_e^2 = (1-\rho)^2\sigma_\eta^2 \tag{6}$$

### 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:

$$E_t \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma} \tag{7}$$

subject to a budget constraint

$$c_t = (w_t n_t + d_t + b_t u_t) = (a_{t+1} n_t - \kappa v_t + u_t b_t) \tag{8}$$

Here $\beta$ is the discount factor, $w_t$ is the real wage, $b_t = a_{t-L+1} b$ is the value of household production for an unemployed worker, and $d_t$ is the profit created by firms. The productivity of household production, which is the opportunity cost of taking a job and determines labour demand, is assumed to lag behind productivity with the reasoning that firms will adopt technology improvements more quickly. However, it is assumed that these technological improvements will eventually diffuse to private households after a number of periods L. The part after the second equal sign in the budget constraint follows from $w_t n_t + d_t = (a_{t+1} n_t - \kappa v_t)$, which follows from the assumptions made in section 3.3.

The expected shadow value of the period budget constraint is $E_t c_t^{-\sigma} = \mu_t$, where $\mu$ is the Lagrangian multiplier on the budget constraint.

### 3.3 Production

Firms are assumed to be identical and to produce goods in period t according to $\Pi_t = a_{t+1} n_t$. Thus firms will have to decide over production in period t without knowing the end of period realization of worker productivity $a_{t+1}$. This assumption is meant to capture the uncertainty over the value that a worker will add to a firm due to uncertainty over the aggregate (productivity) state of the economy, when the management decides to posts and fill a vacancy.

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 $m(v_t, u_t) = m v_t^{1-\xi} u_t^{\xi}$. $m$ 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 $\lambda$. Furthermore, it costs a firm $\kappa_t = \kappa a_{t-L+1}$ to post a vacancy. Admittedly there is no particular empirical reason that hiring costs $\kappa_t$ and the outside value to working $b_t$ should lag behind an equal amount of time. This is merely an assumption that simplifies notation and could be easily relaxed later. The reasoning behind the assumption that the cost of hiring may rise in the long-run with productive technology improvements $a_t$, is that firms will on the aggregate require a more advanced screening process for filling a vacancy and more resources will have to be spent by the firm to integrate the worker in the production process. On a practical modeling side, the assumption $\kappa_t + b_t = (\kappa + b)a_{t-L+1}$ serves to remove the unit root from the match surplus and will thereby provide a steady state level of unemployment which is only shifted by parameter changes of the model and not by productivity shocks (see equation (13)). 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 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 is more workers searching for a job in the current period than the number of unemployed $(1 - n_{t-1})$ in the previous period.

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. :

$$E_t \sum_{t=0}^{\infty} \beta^t \mu_t (a_{t+1} n_t - w_t n_t - \kappa_t v_t) \tag{9}$$

such that:

$$n_t = (1 - \lambda)n_{t-1} + v_t q(\theta_t) \tag{10}$$

The combined first order conditions give the job creation condition where the expected cost of hiring a new worker equals the benefit of hiring a new worker:
$\frac{\kappa_t}{q(\theta_t)} = E_t a_{t+1} - w_t + \beta(1-\lambda)E_t\frac{\mu_{t+1}}{\mu_t}(\frac{\kappa_t}{q(\theta_{t+1})})$
$E_t a_{t+1}$ is the value that the worker is expected to produce in period t. Firms and workers split the expected surplus of a successful match according to Nash bargaining with the firm's bargaining strength being $\pi$. The negotiated wage is then:

$$w_t = \pi b_t + (1-\pi)[E_t a_{t+1} + \beta(1-\lambda)E_t\kappa_t\frac{\mu_{t+1}}{\mu_t}\theta_{t+1}] \tag{11}$$

Substituting equation (12) back into the job creation condition yields:

(12)
$$\frac{\kappa a_{t-L+1}}{q(\theta_t)} = \pi(E_t a_{t+1} - b a_{t-L+1}) + \beta(1-\lambda)E_t[\frac{\mu_{t+1}}{\mu_t}(\frac{\kappa a_{t-L+1}}{q(\theta_{t+1})} - (1-\pi)\kappa a_{t-L+1}\theta_{t+1})]$$

Dividing by $a_{t-L+1}$ finally yields the job creation condition used in the next sections:

$$\frac{\kappa}{q(\theta_t)} = \pi(E_t p_{t+1} - b) + \beta(1-\lambda)E_t[\frac{\mu_{t+1}}{\mu_t}(\frac{\kappa}{q(\theta_{t+1})} - (1-\pi)\kappa\theta_{t+1})] \tag{13}$$

Where $p_t = \frac{a_t}{a_{t-L}}$ is the consumption goods value produced by a filled vacancy relative to the value produced by an unemployed worker, which determines the real profits of the firm. The equation shows that, as mentioned in section 3.2, the value of a worker-firm relationship relative to the value of unemployment will be expected to have a constant steady state as $E_t p_{t+\infty} = E_t\frac{a_{t+\infty}}{a_{t+\infty-L}} = 1$ (see section 3.5 for the value of $E_t a_{t+\infty}$). In other words, the expected value of a filled vacancy and the expected value of unemployment are assumed to be cointegrated. This assumption is the logical consequence of combining the equilibrium of a search and matching model with the empirical observation that output per worker is clearly trending upwards, while the unemployment rate seems to be a stationary series. It is similar to the detrending assumptions for the integrated series made in Schmitt-

Grohé and Uribe (2012).

### 3.4 Aggregate and equilibrium

Market clearing in this simple setting requires that the aggregate constraint of the economy is:

$$c_t = a_{t+1} n_t - a_{t+1-L}(\kappa v_t - b(1 - n_t)) \tag{14}$$

or

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

Equation (15) shows that, while long-run unemployment has an equilibrium level in this model in contrast to the simple model in Blanchard, l'Hullier, and Lorenzoni (2013), the 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 equilibrium equations for the five variables: $c_t, n_t, u_t, \theta_t, v_t$ are:

$$c_t/a_{t+1-L} = p_{t+1} n_t - \kappa v_t + b(1 - n_t) \tag{15}$$

$$\frac{\kappa}{q(\theta_t)} = \pi(E_t p_{t+1} - b) + \beta(1 - \lambda) E_t[\frac{c_{t+1}^{-\sigma}}{c_t^{-\sigma}}(\frac{\kappa}{q(\theta_{t+1})} - (1 - \pi)\kappa\theta_{t+1})] \tag{16}$$

$$n_t = (1 - \lambda) n_{t-1} + v_t q(\theta_t) \tag{17}$$

$$u_t = 1 - (1 - \lambda) n_{t-1} \tag{18}$$

(19) $$\theta_t = \frac{v_t}{u_t}$$

A closer examination of these equations shows that their equilibrium path is fully determined by the parameters $\beta, \lambda, \kappa, \pi, b, \sigma$, 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 $a_{t-L+1}, ..., a_t, E_t a_{t+1}, E_t a_{t+2}, ....$ .

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 equations at this steady state with a first order log-linearization yields:

(20) $$\hat{c}_t = \frac{n}{c}[\hat{p}_{t+1} + \hat{n}_t] - \frac{\kappa v}{c}\hat{v}_t - \frac{bn}{c}\hat{n}_t + \hat{a}_{t+1-L}$$

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

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

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

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

(24) $$\hat{\theta}_t = \hat{v}_t - \hat{u}_t$$

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.

$$\hat{\theta}_t = \psi_1 E_t \hat{p}_{t+1} + \psi_2 \psi_1 E_t \hat{p}_{t+2} + \psi_2^2 E_t \hat{\theta}_{t+2} = \psi_1 E_t \sum_{s=0}^{\infty} \psi_2^s \hat{p}_{t+1+s} \tag{25}$$

$$\hat{v}_t = \psi_1 E_t \sum_{s=0}^{\infty} \psi_2^s \hat{p}_{t+s} + \frac{(1-\lambda)n}{1-(1-\lambda)n} \hat{n}_{t-1} \tag{26}$$

This result is generalized to values of $\sigma \geq 0$ by inserting equation (23) and (24) into equation (21), and the resulting equations into (22) 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 $a_{t+1}$ and $p_{t+1}$ would be part of their information set in period t, hiring in the current period will still depend on the future productivity expectations $E_t p_{t+2}, E_t p_{t+3}, ....$ 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.// All that is left for determining the current equilibrium level of vacancies, employment, consumption, and output, and thereby solving the model, is to find the path of future productivity expected by the agents.

### 3.5 Forming expectations over future productivity

It is assumed that all agents have the same information set. They observe last periods employment and labour market tightness. They also observe past productivity values $a_{t-s}, s \geq 0$, as well as signals on the permanent part of productivity $s_t$. Furthermore, agents have correct assumptions over the processes determin-

ing productivity and the relevant parameters describing these processes. If agents wouldn't receive an informative signal then the choice of parameters $\rho^x, \rho^z, \sigma_e^2, \sigma_\eta^2$ would have the consequence that expected future productivity would be equal to current productivity as shown in Blanchard, L'Huillier, and Lorenzoni (2013). 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. There is also no information in past signals beyond the past expected values of the permanent ($x$) and temporary ($z$) component of worker productivity $a$ .

However, 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, which rational agents solve by Kalman filtering the information provided. Thus agents observe $a_{t-s}, s \geq 0$ and $s_t$, and based on this information they form expectations over $a_{t+s}, s \geq 1$.

The agent Kalman filter thus works in the following way. Agents know that there is an unobserved process of the form:

$$\begin{bmatrix} x_t \\ x_{t-1} \\ z_t \end{bmatrix} = \begin{bmatrix} 1+\rho & -\rho & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} e_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{27}$$

Meanwhile agents observe only $a_t$ and $s_t$ which are driven by the same shocks according to:

$$\begin{bmatrix} a_t \\ s_t \end{bmatrix} = \begin{bmatrix} (1+\rho) & -\rho & \rho \\ (1+\rho) & -\rho & 0 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{28}$$

Finally expectations on the permanent and temporary component of $a_t$ have to ad

up to $a_t$ and the signal is a combination of news and noise:

$$\begin{bmatrix} a_t \\ s_t \end{bmatrix} = D \begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} + \begin{bmatrix} 0 \\ \nu_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} + \begin{bmatrix} 0 \\ \nu_t \end{bmatrix} \tag{29}$$

Given these identities the result of the agent Kalman filter is:

$$\begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} = \begin{bmatrix} 1+\rho & -\rho & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho \end{bmatrix} (I - KD) \begin{bmatrix} x_{t-1|t-1} \\ x_{t-2|t-1} \\ z_{t-1|t-1} \end{bmatrix} + K \begin{bmatrix} a_t \\ s_t \end{bmatrix} \tag{30}$$

Where I is the identity matrix, K is the converged Kalman gain and a 3x2 matrix, as agents are assumed to know the parameters of the productivity and noise process. Given that the covariance matrix of the shocks is positive semi-definite, as the three shocks $e, \eta$ and$\nu$ are independent the Kalman gain will converge (Anderson, Hansen, McGrattan, and Sargent, 1996). Each element of the Kalman gain is a function of the parameters $\sigma_e, \sigma_\nu$ and $\rho$.

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

Then the equation for updating equations can be summarized by:

$$\begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \end{bmatrix} = T \begin{bmatrix} x_{t-1|t-1} \\ x_{t-2|t-1} \\ z_{t-1|t-1} \end{bmatrix} + K \begin{bmatrix} a_t \\ s_t \end{bmatrix} \tag{32}$$

Where T is the 3 by 3 matrix:

(33)
$$T = \begin{bmatrix} (1+\rho)(1-K_{11}-K_{12})+\rho(K_{21}+K_{22}) & -\rho & -(1+\rho)K_{11}+\rho K_{21}) \\ 1-K_{11}-K_{12} & 0 & -K_{11} \\ -\rho(K_{31}+K_{32}) & 0 & -\rho K_{31} \end{bmatrix} = T(\sigma_e, \sigma_\nu, \rho)$$

As mentioned above the steady state of $a_{t-L}$ is assumed to be normalized to 1. Based on the estimated values of $x_{t|t}, x_{t-1|t}, z_{t|t}$ agents form their expectations over future productivity:

$$a_t = x_{t|t} + z_{t|t}$$

$$E_t(a_{t+1}) = (1+\rho)x_{t|t} - \rho x_{t-1|t} + \rho z_{t|t}$$

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

Converging in the long-run to:

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

For the long-run value of the contribution of a firm worker relationship to consumption this means:

(34)
$$E_t(p_{t+\infty}) = \frac{E_t(a_{t+\infty})}{E_t(a_{t-L+\infty})} = 1$$

With equations (27), (28) and (30) the expectations about future productivity growth can be described as the result of current expectations and the fundamental shocks $e$, $\eta$, and $\nu$.

### 3.6 State space form

Combining the results from section 3.5 and 3.6 allows representing the approximated 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 variable ($\theta$).

$$AE_t \begin{bmatrix} \theta_{t+1} \\ n_t \\ x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ x_t \\ x_{t-1} \\ z_t \\ \dots \\ x_{t-L+1} \\ z_{t-L+1} \end{bmatrix} = B \begin{bmatrix} \theta_t \\ n_{t-1} \\ x_{t-1|t} \\ x_{t-2|t} \\ z_{t-1|t} \\ x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ \dots \\ x_{t-L} \\ z_{t-L} \end{bmatrix} + C \begin{bmatrix} e_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{35}$$

The first two rows and columns of matrix A and B are given by equations 21, 22, 28 and 30. Meanwhile the lower right part 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 $\sigma_e$, $\sigma_\nu$ and $\rho$. Estimating these parameters is the central aim of this model. Observe that in the special case where $L = 1$ the number of state variables collapses to 7.

# 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 and noise $\sigma_e, \sigma_\nu$ in the labour market as well as the persistence of shocks $\rho$ are estimated below by maximizing the like-

lihood 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 an 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 hirings are most likely the result of noise. For the productivity series, changes in real and potential 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. All data series are taken from the online database of the Federal Reserve Bank of St. Louis (FRED) and the series code is given in square brackets.

**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. As explained below in section 4.4 for estimation purposes it will be assumed to that $\Delta a_t + \tau = \Delta p_t$, where $\tau$ is a linear trend of $a_t$.

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 $\frac{Y_t}{N_t} = A_t(\frac{K_t}{N_t})^{\alpha}$. Here $K_t$ 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 result of 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.

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.

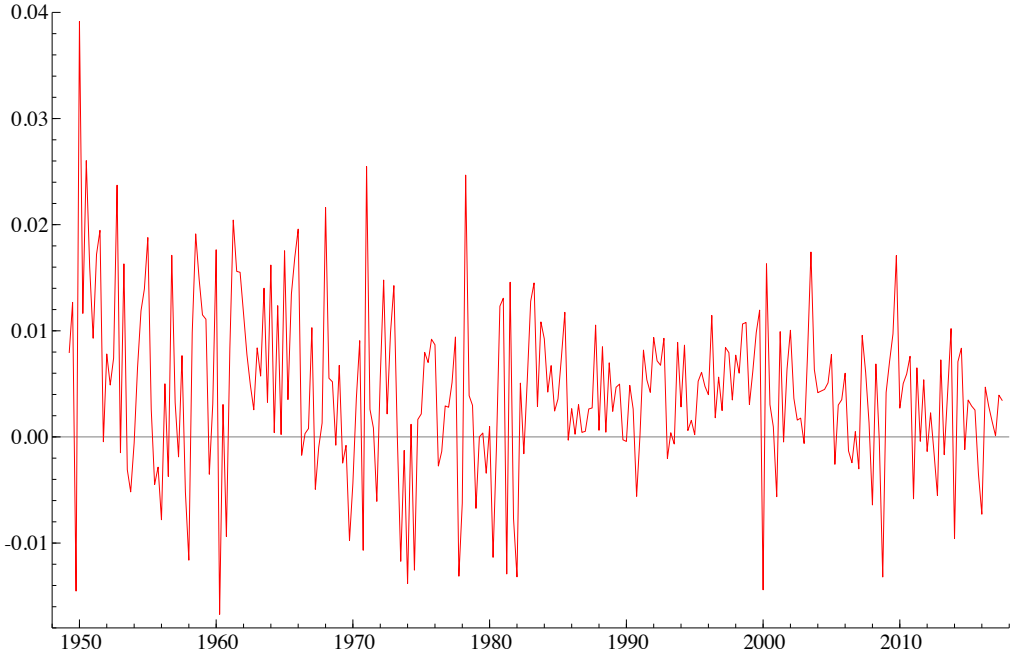
One can test whether the random walk assumption of the model is plausible for the output per worker series $a_t$. This is done by testing the hypothesis that for the AR(1) process $\Delta a_t = \mu_a + \rho_a \Delta a_{t-1} + u_t$ the estimated coefficient $\hat{\rho}_a = 0$. An estimation of $\hat{\rho}_a$ with ordinary least squares based on the data on US real output per person of non-farm businesses between the second quarter of 1949 and the third quarter of 2017 gives 0.055 with a standard error of 0.06. Given that the t-value is 0.91, while the critical values of the Dickey-Fuller distribution for a series with a constant and trend such as this one are all negative, the random walk assumption for $a_t$ is clearly rejected. This means that there is some residual information in present values of a for future values. This residual information may be ignored for now as it seems small, but since it is significant a further more precise investigation into the noise component in labour market decision making may require to address this issue by generalizing the agent Kalman filter for cases where productivity is a unit root process, but not a random walk.

The productivity series on which the estimation is based is presented in figure 1.

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

To find the job-finding-rate I employ the procedure suggested in Shimer (2005). I

**Figure 1:** Changes in Labour productivity $\Delta a_t$ based on Output[GDPC1] per Worker[PAYEMS]




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 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

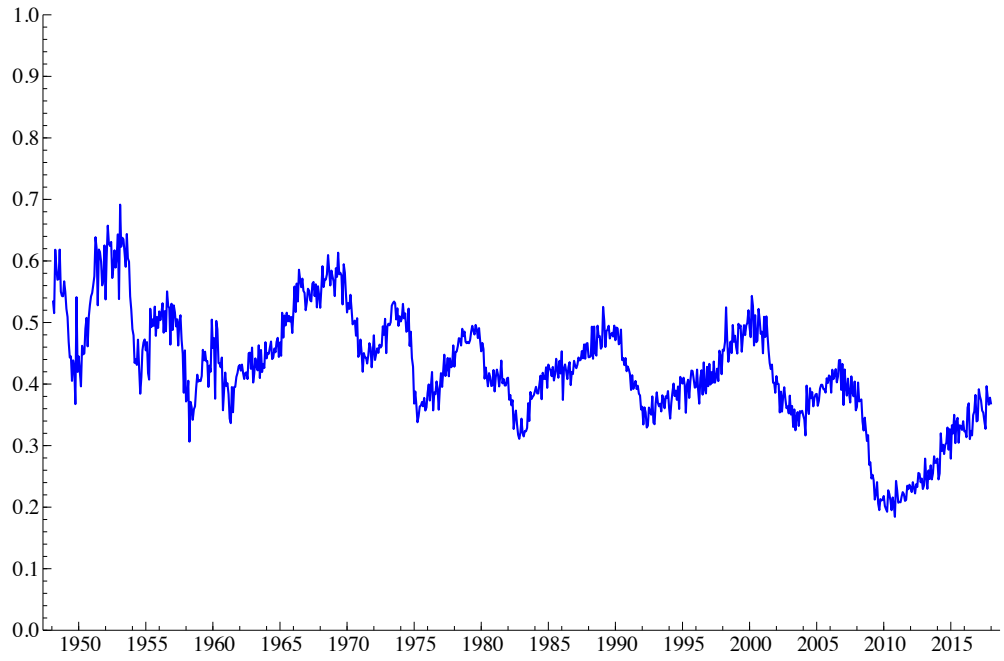
$$f_t = 1 - \frac{U_t - S_t}{U_{t-1}}$$

, 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] are 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 job finding rate estimated by this procedure is plotted in figure 3.

**Figure 2:** Monthly job-finding Rate $f_t$

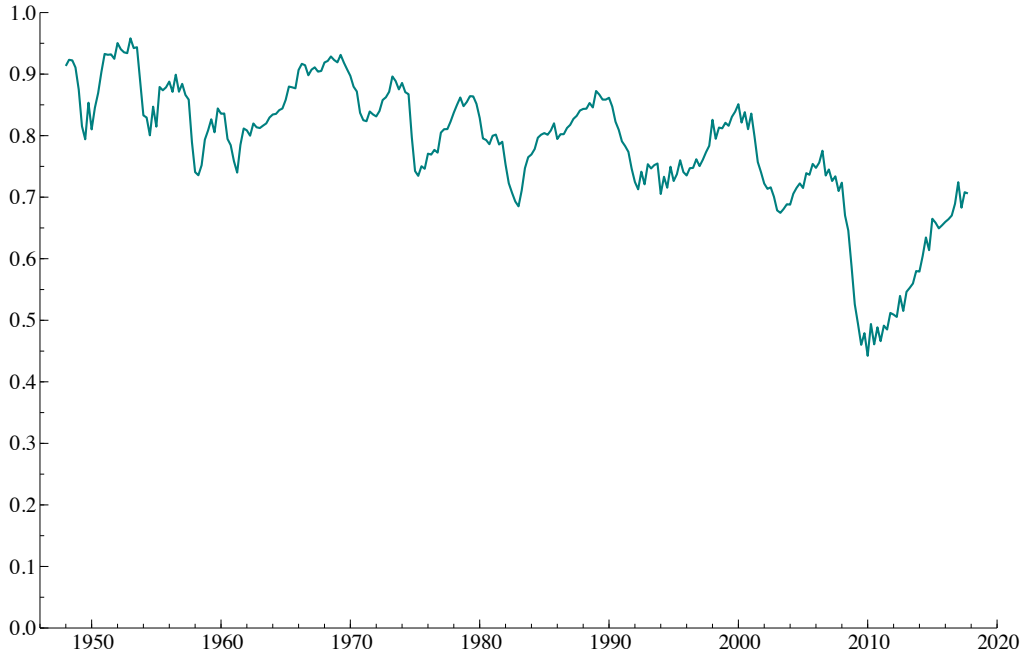



Due to a lack of data on monthly productivity for the sample these transition probabilities have to be transformed to quarterly transition probabilities. The transformation is done by calculating the probability of the worker of not finding a job in the past three months and subtracting this from 1. $p(\theta_t) = 1-(1-f_t)(1-f_{t-1})(1-f_{t-2})$ This series in figure 4 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 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

**Figure 3:** Quarterly job-finding Rate p($\theta_t$)




series levels.

## 4.2 Calibration of the model

Naturally this simplified model will not be able to generate the same data for the labour market as the complex data generating process at work in the US labour market, where employment decisions depend on a the state of a larger amount of variables. For this reason it is necessary to calibrate the model such that its dynamics reflect the US labour market, if the impulse response functions and estimated parameters of news and noise shocks in the model are to be good descriptors of reality.

Based on monthly data between 1949 and the end of 2017 the average unemployment rate for the US was 5.83%. The average monthly job-finding probability was 0.425 (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 $1 - (1 - 0.425)^3 = 0.78$.

Taking the assumed law of transition in the model, this corresponds to a quarterly separation rate $\lambda$ of 0.26. Thus about half of the jobs created only last half a year. 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 witht 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 on 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 $m = 0.77$. Hagedorn and Mavoskii (2008) estimate that the weekly 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 $\kappa$ should be set to 0.0365. Given this the value of home production should be set to $b = 0.8825$. Worker bargaining power is chosen such that it is socially efficient, which requires that it fulfils the Hosios condition (Hosios 1990) $\xi = 1 - \pi$.

### 4.3 Simulated impulse response

The impulse response functions of the model have been simulated with the parameters in Table 1, which result in an equilibrium employment rate of 94.21% in equilibrium. Similar to Den Haan and Kaltenbrunner (2009) the payments necessary to create a new job ($\kappa$) are interpreted as investment. The figures below show the impulse response functions of output ($y_t = p_t n_t + b_t(1 - n_t)$), employment ($n_t$), investment ($\kappa_t v_t$), consumption ($c_t$), and the job-finding rate ($p(\theta_t)$) as well as the actual path of worker productivity, the expected long-run productivity value, and the expected permanent component of current productivity $E_t(x_t) = a_t - E_t(z_t)$. The variance of the permanent component and the noise shock have been set to equal levels so that disentangling noise and news is the most difficult for agents. For this relation a signal may have been at equal probabilities the result of news or the result of noise. The values for $\rho$ and $\sigma_e^2$ are close to the maximum likelihood results for the productivity process and it's persistence with regard to agent consumption choices in Blanchard, l'Huillier and Lorenzoni (2013) which are 0.89 and 0.0007. With the chosen values the standard deviation of the change in employment is 0.0038 in the simulated model and 0.00384, which is an argument for the calibration choices made in section 4.2 and 4.3 as these lead to similar dynamics as can be observed in the data.

Except for the parameters one also has to make a choice over the length of the period with which the (opportunity) cost parameters $\kappa_t$ and $b_t$ lag behind in productivity. Since the choice is largely arbitrary the impulse response functions will present two cases. The first is the case when the lag is so large that the reaction is negligible. The second case presented shows the impulse response when the parameters lag 12 quarters behind thus $\kappa_t = a_{t-12}\kappa$ and $b_t = a_{t-12}b$. The first five graphs of figures 6-8 show in blue the impulse response under the assumption that the lag on $b_t$ and $\kappa_t$ is so large that the lag component doesn't influence short-run decision making, while the black dashed line shows the impulse response for L=12. The purpose of the model with 12 lags is to demonstrate that the impulse response

to productivity shocks for a finite lag model is similar to the impulse response of a positive followed by a smaller negative shock for the variables of unemployment and the job-finding rate on which the estimation of the model parameters will be based on. For this reason the estimation of the model parameters will be based on the demeaned productivity series, which will be expected to stay in the long-run in a constant relation to $\kappa$ and $b$ without the need of imposing a specific lag length.

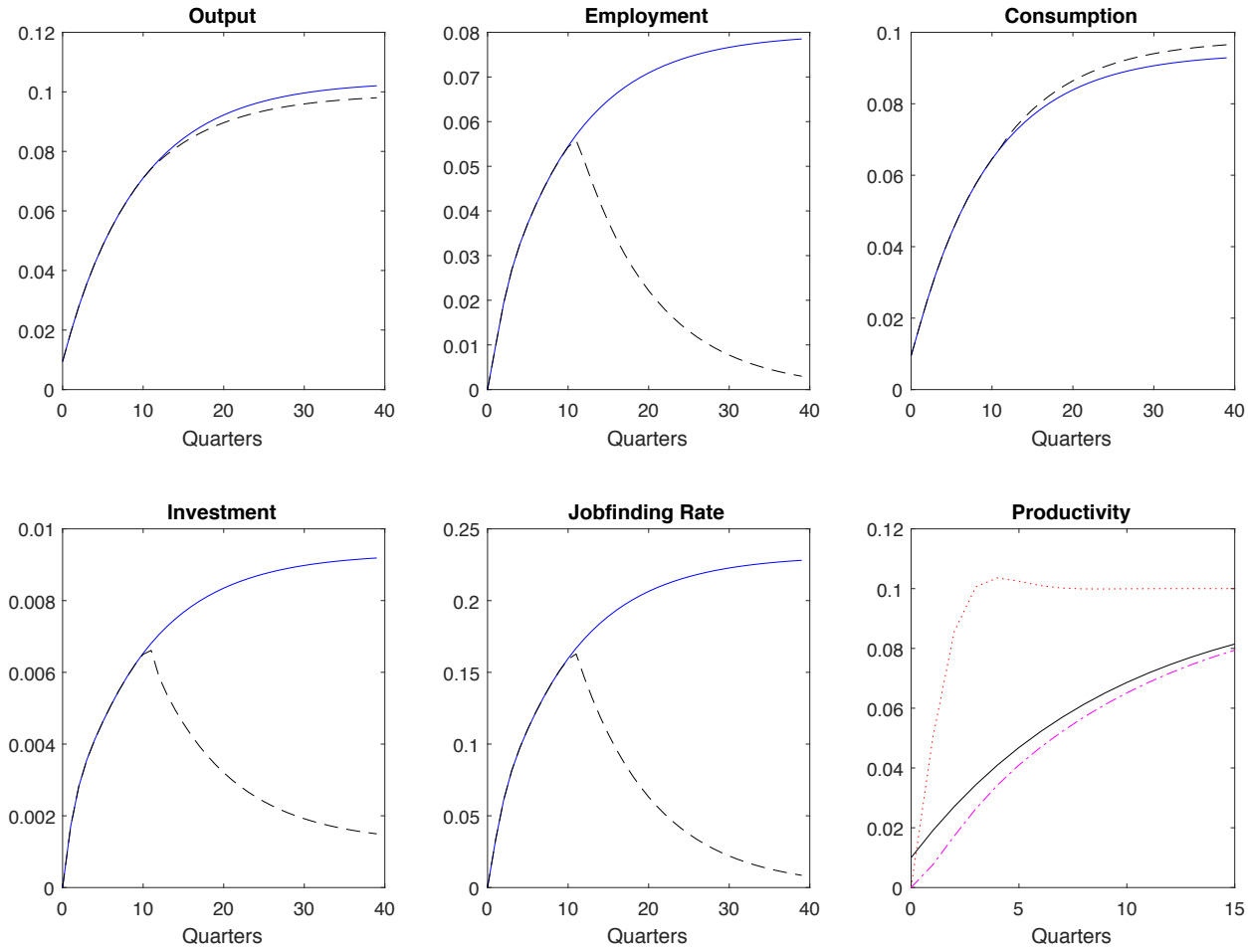
The sixth graph in figures 6 to 8 shows the path of actual worker productivity $a$ (black line), the expected long-run value of the permanent component (red dotted line), and the expected value of the permanent component at time t (magenta dashed line).

Figure 1 shows the impulse response function to a 1% shock to the permanent component $x_t$, while Figure 2 shows the same for $z_t$ and Figure 3 for $s_t$ as a result of a noise shock $\nu_t$.

**Table 1:** Parameters for the simulation

| $\beta$ | $\sigma$ | $m$ | $\xi$ | $\pi$ | $\lambda$ | $b$ | $\kappa$ | $\rho$ | $\sigma_e^2$ | $\sigma_\nu^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.99 | 1 | 0.77 | 0.7 | 0.3 | 0.25 | 0.8825 | 0.0365 | 0.9 | 0.0006 | 0.0006 |

**Figure 4:** Responses to a shock to the permanent component ($e_1$)




Kursell and McKay (2010) point out that a simple search and matching model is able to produce Pigou cycles in response to news shocks. This property can also be observed in the model presented as a shock to the permanent component of productivity, which entails a surprise productivity shock in period 0 and a news shock about expected future productivity growth creates a positive co-movement of consumption, employment and investment. The shock to productivity in period 0 will have come as a surprise and will thereby increase consumption and output. In period 1 agents will observe the increased value of productivity (a) and will additionally receive a noisy signal over permanent or temporary the nature of the productivity shock. Based on this signal agents form expectations over the future

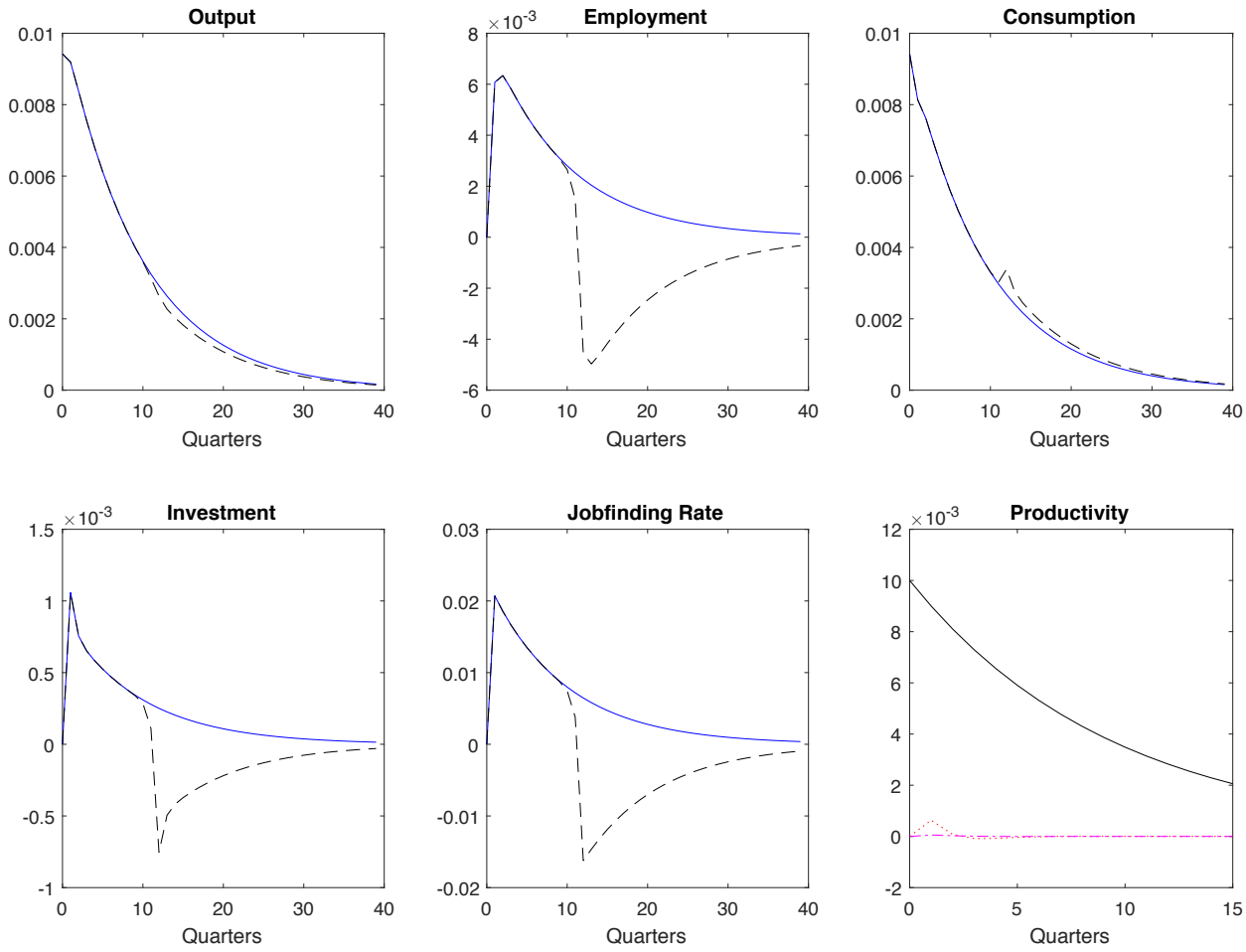
productivity of a firm-worker relationship and firm's will increase hiring due to the increase in past productivity and the shift in expectations about future productivity. The purpose of the sixth graph is to show the gradual shift in expectations about future productivity due to the signal extraction problem faced by agents.

A shock to the permanent component of productivity in period 0 will mean that productivity changes in the long- run from $\frac{x_t - \rho x_{t-1}}{1-\rho}$ to $\frac{x'_t - \rho x_{t-1}}{1-\rho} = \frac{x_t - \rho x_{t-1}}{1-\rho} + \frac{1}{1-\rho} e_t$. Without noise a shock of size e would thus add immediately $\frac{1}{1-\rho} e = 0.01/0.1 = 0.1$ to the expected long-run value of worker productivity $E_t(a_{t+\infty})$, which would result in a horizontal red dotted line in the sixth graph. However, due to the noise in the signal agents are unsure whether they observe information about an actual change in the permanent productivity component or just noise. Similarly, agents do not know whether the increase in observed worker productivity ($a_t$) is due to a shock to the permanent productivity component ($x_t$) or due to the temporary component ($z_t$). To disentangle noise from news as well as possible the agents use the Kalman filtering, as described in section 3.5. As time passes agents learn whether the signal was in fact news and their expectation of long run productivity will slowly increase and converge with the actual level of long-run productivity.

Through this process, the noise component in the signal will lead to less hiring and a gradual adjustment to the new equilibrium employment level as firms and workers gradually learn about the actual change in the value that a filled vacancy creates in comparison to home production. When the productivity of home production and the cost of posting a vacancy begin to adjust after 12 quarters, no new information on the future productivity path is revealed. For this reason the model with the impulse response functions with the dashed black lines will simply follow a path where employment and the job-finding rate return to equilibrium after 12 periods. This increase in unemployment as growth stagnates towards 0 is coherent with the empirical observations that led to the formulation of Okun's law (Okun 1962). In this process of declining employment, output growth will decelerate, but consumption growth will increase due to the decrease in investment as less vacan-

cies are being posted.

**Figure 5:** Responses to a shock to the temporary component ($\eta_1$)




With regard to a shock to the temporary component $z_t$ in period 0, a similar mechanism is at work. 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. Given that agents receive no signal that the permanent component has increased, but the signal might have been drowned out by noise long-run productivity, expectations rise. This can be seen in the small bump of the red dashed line. However, as the signals in the next periods also do not

show that the permanent component has increased, agents become increasingly convinced that the productivity shock was of a temporary nature.

With regard to the impulse response function of the labour market the agents follow the following decision making process. Due to temporary productivity shocks being expected to have some persistence as given by $\rho$ combined with the possibility of a rise in the permanent productivity component, firms will increase hiring. 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 wealth effect leading to increased labour demand. As the temporary component vanishes over time, output, consumption, and employment return to equilibrium. In the case of the lagged adjustment of the value of unemployment and vacancies (dashed black lines in graphs 1-5) after twelve quarters the effect is similar to a known temporary negative shock to productivity. This further strengthens the case for basing the estimation of the news and noise parameters just on a detrended path of worker productivity and to ensure with this detrending that the steady state relation of the product of a firm-worker relationship, the cost of posting a vacancy, and the value of home production remain constant in the long run.

**Figure 6:** Responses to a noise shock ($\nu_1$)

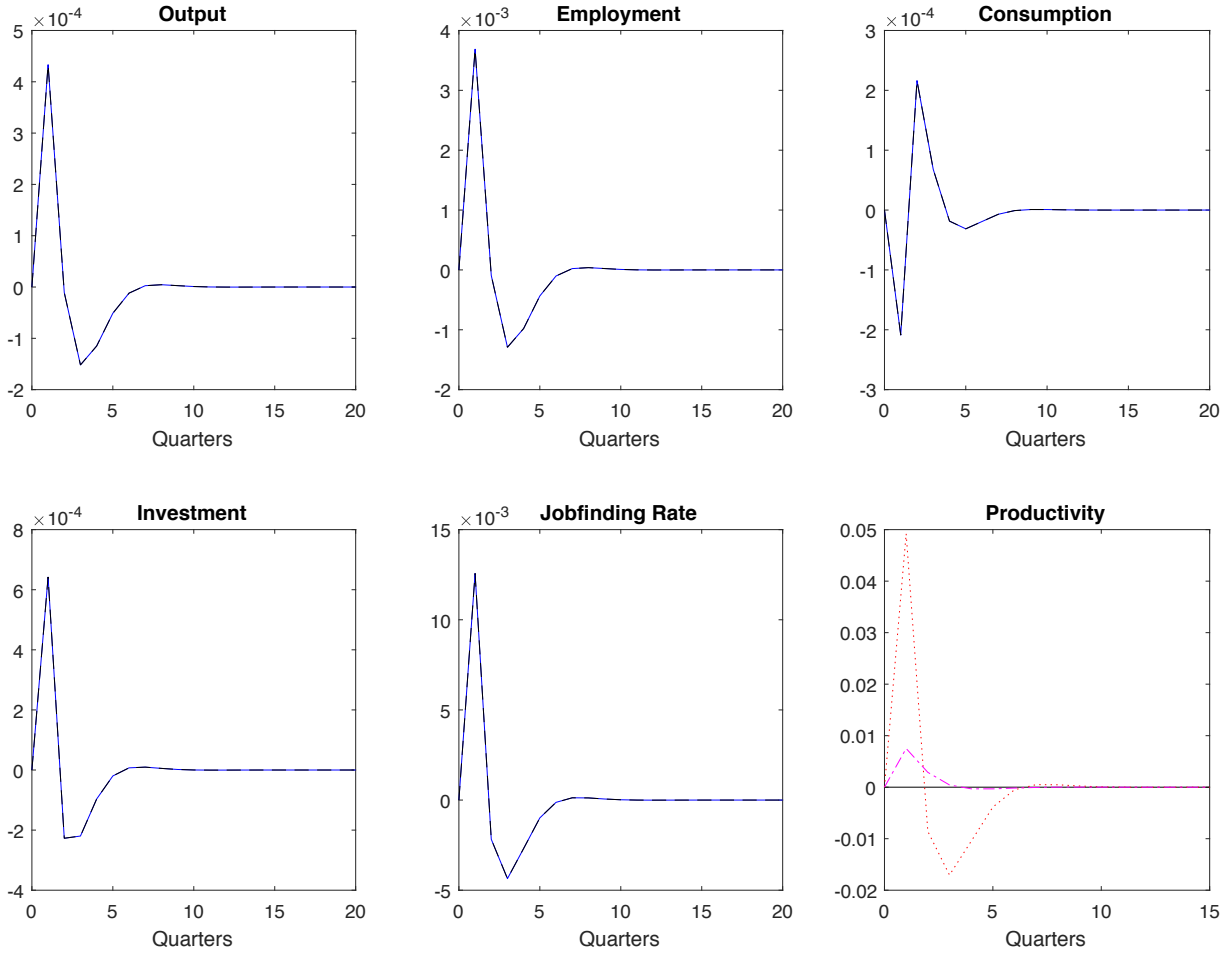



Figure 7 finally shows the impulse response functions caused by a noise shock. Actual worker productivity remains flat, but the noise shifts the expectation over the size of the long-run component $x_t$. The reason that agents do not observe the supposed shock to $x_t$ could be that a negative shock to the temporary component $\eta_t$ had occurred at the same time. Thus 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. 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 to a decrease in employment and an increase in consumption.

The variance decomposition in table 2 shows that under the given calibration noise may contribute substantially to employment fluctuations in the short-run. Thus theoretically almost 10 % of the changes in employment in the first quarter may be caused by noise. However, for longer term forecasts the permanent component becomes quickly the most important driver of fluctuations.

**Table 2:** Variance decomposition of the employment rate

| Quarters | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Permanent ($e$) | 65.36% | 83.79% | 90.37 % | 93.53 % |
| Temporary ($\eta$) | 25.32% | 13.78 % | 8.47 % | 5.79% |
| Noise ($\nu$) | 9.32% | 2.43 % | 1.16 % | 0.68 % |

### 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. Using the Kalman smoother estimation can only be successful based on two series at once as there are only two independent innovations in the form of productivity and noise shocks. For this reason only the parameters of the news and noise processes are estimated, while the labour market parameters are set via the calibration described above. Two series cannot be expected to contain enough information to identify parameters such as the matching cost $\kappa$ or the matching productivity $m$ together with the shock parameters. The demeaning of the processes substitutes for making a concrete assumption over the lag with which $\kappa_t$ and $b_t$ adjust to a productivity shock $a_t$. These adjustments will instead show up as shocks sending worker productivity back to the equilibrium trend.

The underlying assumption for demeaning the productivity is that the value of a filled vacancy and the value of unemployment are cointegrated and unemployment is therefore a stationary series. For this to be the case in the model $a_t, b_t$ and $\kappa_t$ have to follow the same long-run trend. It is further assumed that this trend is linear and that when $a_t$ is above trend $p_t$ is larger than 1, while when $a_t$ is below trend it is below 1. The expected change of $a_t$ in the long run is then 0 and the steady state of worker productivity (p) will therefore be 1. Agents form expectations over the path of the productivity of a a firm-worker relationship in comparison to home production equilibrium $E_t p_{t+1+s}$ and firms will post vacancies based on these expectations. The results of the maximum likelihood estimation of the news and noise parameters are presented in table 3.

**Table 3:** News and nosie parameters

| ML Estimation based on: | job-finding rate (p($\theta_t$)) | Unemployment (1-n) |
|---|---|---|
| $\rho$ | 0.818 (0.01) | 0.8623 (0.0072) |
| $\sigma_e$ | 0.0086 (0.00033) | 0.0063 (0.00025) |
| $\sigma_\eta$ | 0.043 (0.0016) | 0.0428 (0.00017) |
| $\sigma_\nu$ | 0.0005 (0.0003) | 0.0004 (0.0002) |

**Table 4:** Variance decomposition of the employment rate based on the estimation on job-finding rate/Unemployment

| Quarters | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Permanent ($e$) | 95.18/91.03% | 97.1/94.42% | 98.1/96.27 % | 98.7/97.36 % |
| Temporary ($\eta$) | 4.71/8.84% | 2.85/5.52 % | 1.88/3.7 % | 1.3/2.6% |
| Noise ($\nu$) | 0.11/0.13% | 0.05/0.06 % | 0.02/0.02 % | 0.01/0.02 % |

The estimation suggests that on the occasions on which agents receive information about the future, the information is usually correct. Thus, agents react rapidly to changes in the expected future productivity of a worker-firm relationship. There is little to no noise in the 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 VAR estimation of the importance of noise in job creation

Forni et. al (2017) suggest alterations to the assumptions in Blanchard, l'Hullier, and Lorenzoni (2013). If these assumptions hold, then it is possible to identify noise shocks with a structural VAR model, something that is attempted 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 certain number of periods whether a past signal was news or noise. In contrast, in Blanchard, l'Hullier, and Lorenzoni (2013) agents only ever know with an increasing probability the true nature of past shocks. If agents are able to identify noise shocks, then the econometrician may 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 Structural model

The process determining worker productivity is assumed to be a random walk with a drift $\tau$.

(36) $$[a_t = a_{t-1} + \tau + \epsilon_{t-S}$$

$\epsilon_{t-S}$ is a news shock determined 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 $\rho$ 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 3.1 in each period agents are assumed to observe worker productivity $a_t$ and to receive a noisy signal over a future innovations of the form:

(37) $$[s_t = \epsilon_t + \nu_t$$

Again there is assumed to exist some form of cointegration 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 $a_t$.

(38) $$\Delta p_t = \Delta a_t - \tau = L^S \epsilon_t$$

The agents are assumed to know that both $\epsilon_t$ and $\nu_t$ 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:

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

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:

$$E(p_{t+\infty} - p_t | I_t) = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} \sum_{i=0}^{S} s_{t-i} \tag{40}$$

Given the equilibrium described in section 3.4 and the state space form discussed in 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.

$$[\theta_t = \theta^* + \phi_{0,1}(n^* - n_{t-1}) + E_t \sum_{i=0}^{\infty} \phi_{0,2+i} \Delta p_{t+1+i} + e_{3,t} \tag{41}$$

or

$$p(\theta_t) = p(\theta^*) + n^* + \phi_{1,1}(n^* - n_{t-1}) + E_t \sum_{i=0}^{\infty} \phi_{1,2+i} \Delta p_{t+1+i} + e_{3,t} \tag{42}$$

Finally using equation 40

$$p(\theta_t) = p(\theta^*) + n^* + \phi_{1,1}(n^* - n_{t-1}) + \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} \sum_{i=0}^{S} \phi_{1,2+i} L^i s_t \tag{43}$$

where $\theta^*$ 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 unemployment can be captured by the equation

$$n_t = n^* + \phi_{2,1}(n^* - n_{t-1}) + \phi_{2,2}(p(\theta^*) - p(\theta_t)) + e_{4,t} \tag{44}$$

The structural VAR system is then:

$$(45)\quad \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{-\sigma_\epsilon^2}{\sigma_\epsilon^2+\sigma_\nu^2}\sum_{i=0}^{S}\phi_{1,2+i}L^i & 1 & 0 \\ 0 & 0 & \phi_{2,2} & 1 \end{bmatrix} \begin{bmatrix} \Delta p_t \\ s_t \\ p(\theta_t) \\ n_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ p(\theta^*)+\phi_{1,1}n^* \\ (1+\phi_{2,1})n^*+\phi_{2,2}p(\theta^*) \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\phi_{1,1} \\ 0 & 0 & 0 & -\phi_{2,1} \end{bmatrix} \begin{bmatrix} \Delta p_{t-1} \\ s_{t-1} \\ p(\theta_{t-1}) \\ n_{t-1} \end{bmatrix} + \begin{bmatrix} L^S & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \nu_t \\ e_{3,t} \\ e_{4,t} \end{bmatrix}$$

This model has a clear ordering. The job-finding rate will affect employment contemporaneously, but not vice versa.

## 5.2 Identification and estimation of the effect of noise

To estimate the model the two labour market series $p(\theta)$ and $(n_t)$are demeaned. An instrument needs to be chosen to measure the signal that is not observed directly. The chosen instrument $z_t$ is the expectation of business conditions in a year from the Surveys of Consumers by the University of Michigan. 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 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. 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 is run to find the innovations of this representation:

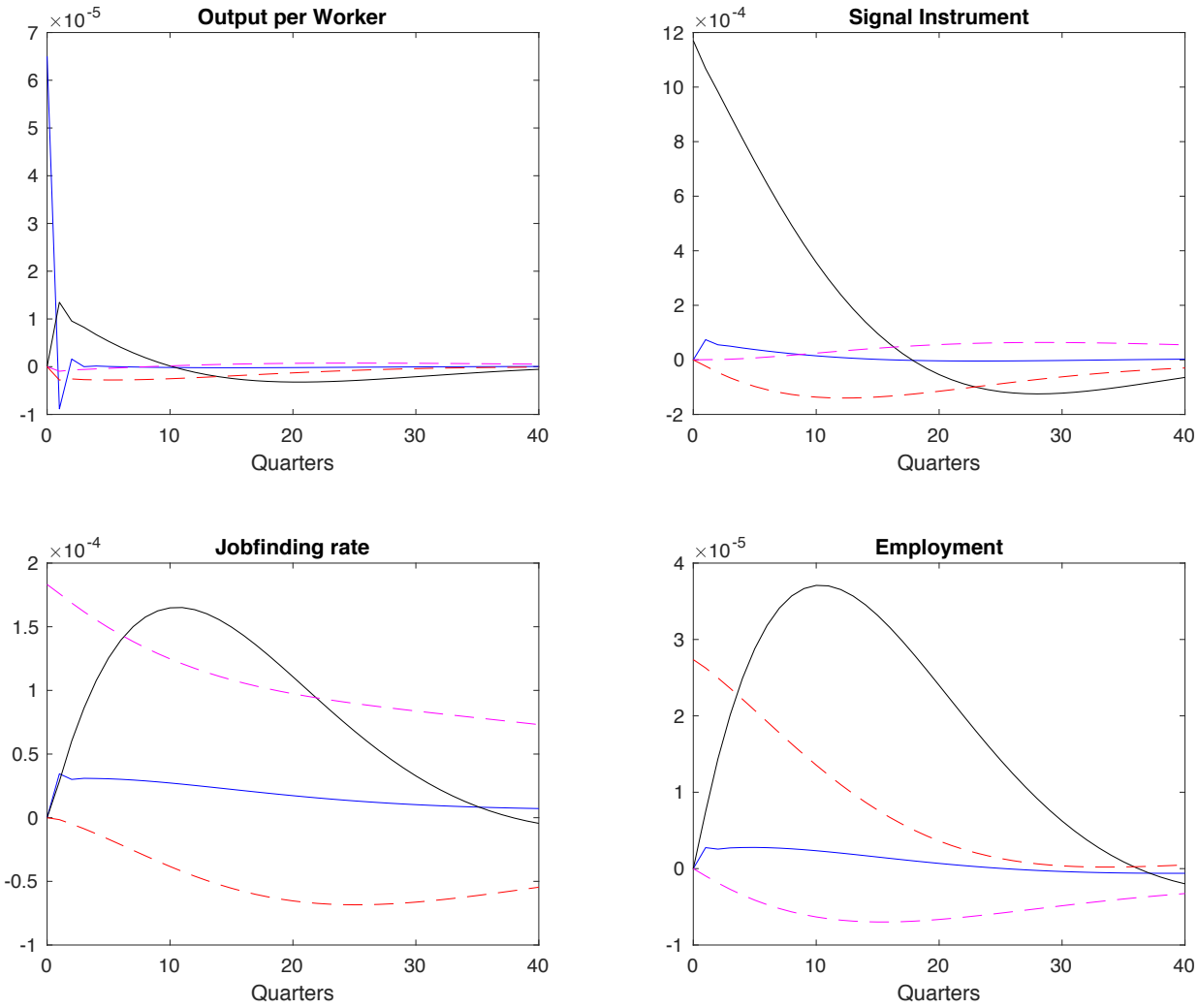
$$(46)\quad \begin{bmatrix} \Delta p_t \\ z_t \\ p(\theta_t) \\ n_t \end{bmatrix} = A \begin{bmatrix} \Delta p_{t-1} \\ z_{t-1} \\ p(\theta_{t-1}) \\ n_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ s_t \\ x_{3,t} \\ x_{4,t} \end{bmatrix}$$

Here $u_t$ is a surprise shock. $s_t$ is a change in the signal. Meanwhile $x_3$ and $x_4$ are separate shocks that may also affect the observed variables and may be a combina-

tion of the shocks $e_3$ and $e_4$ described above. The MA representation of the process above is:

$$\begin{bmatrix} \Delta p_t \\ z_t \\ p(\theta_t) \\ n_t \end{bmatrix} = \sum_{i=0}^{\infty} A^i L^i \begin{bmatrix} u_t \\ s_t \\ x_{3,t} \\ x_{4,t} \end{bmatrix} \tag{47}$$

**Figure 7:** Impulse responses to a 1% standard deviation shock $u_t$ (blue), $s_t$(black), $x_3$ (magenta) and, $x_4$ (red)




The impulse response functions of either innovation are presented below in figure 8. Especially the black (signal shocks) and the blue line (surprise productivity) are of interest. In this representation, which is assumed to be fundamental, output per worker reacts strongly to surprise shocks in the period of the shock, which would be expected. The reaction of the job finding rate and employment to a surprise productivity shock is also positive as would be expected, even though it is weak.

Positive signal shocks are, as one would hope, the main drivers of the signal instrument. The shocks also have a limited effect on output per worker several periods ahead, which is in line with the structural assumptions. The shocks also increase the job finding rate and employment as would be expected. The persistence of the effect of the shocks is, however, much larger than would be expected from the structural assumptions.

As suggested by Forni et. al. (2017) the structural shocks $\epsilon_t$ and $v_t$ can be recovered from the shocks of the fundamental representation $u_t$ and $s_t$ by using the structural assumptions 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 described by equation 48.

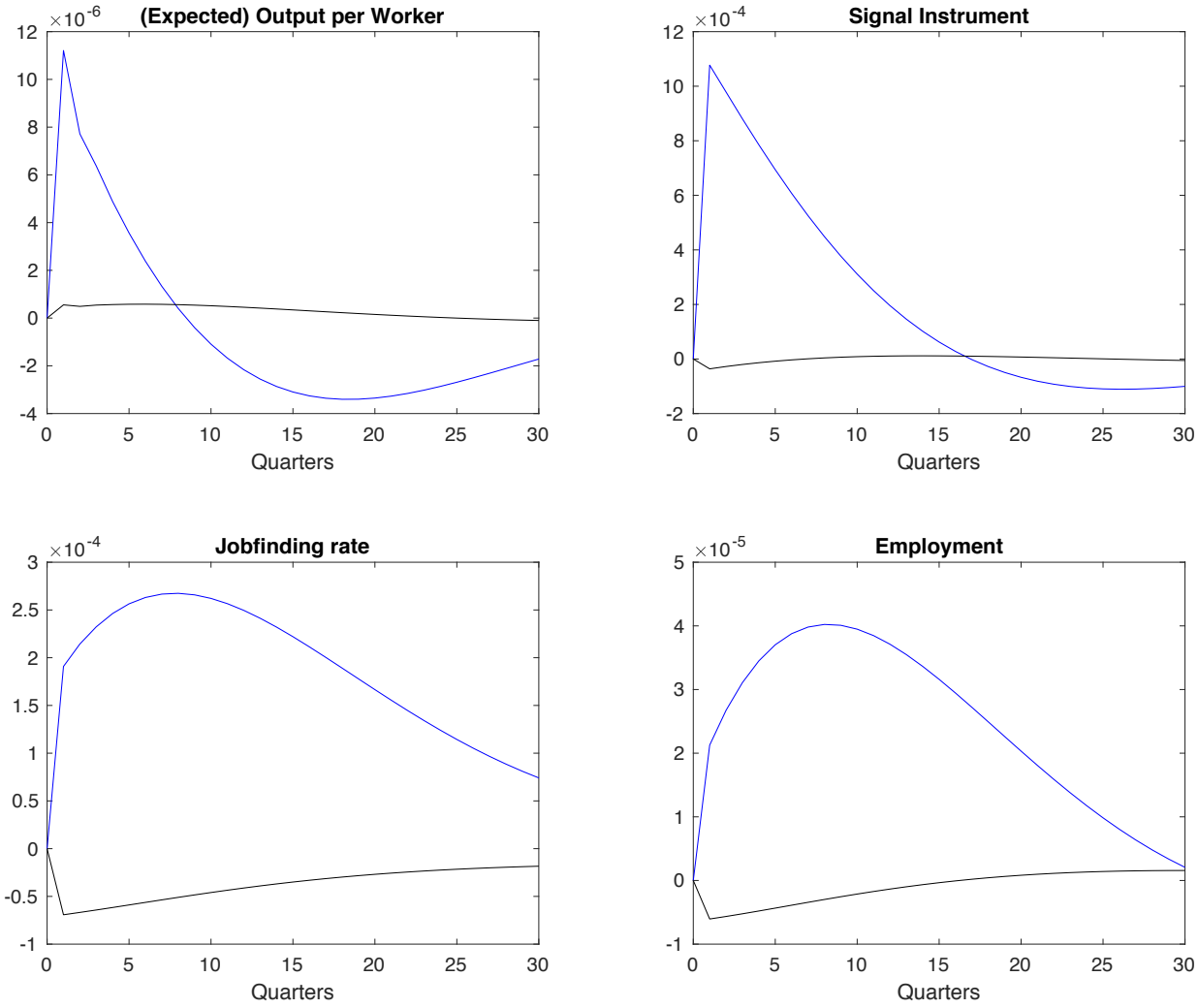
$$\begin{bmatrix} \epsilon_t \\ \nu_t \end{bmatrix} = \begin{bmatrix} L^4 & \frac{\sigma_\epsilon^2}{\sigma_s^2} \\ -L^4 & \frac{\sigma_\nu^2}{\sigma_s^2} \end{bmatrix} \begin{bmatrix} u_t \\ s_t \end{bmatrix} \tag{48}$$

$\sigma_s$ 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 $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = \hat{B}_{1,2}/\hat{B}_{1,1}$, where $\hat{B} = \hat{A}^4$. 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 $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = 0.94$ and $\frac{\hat{\sigma}_\epsilon}{\hat{\sigma}_\nu} = 0.35$. Finally, Forni et. al. (2017) suggest to transform the fundamental representation to the structural representation by post-multiplying the MA process in equation 47 with the matrix C.

(49)
$$C = \begin{bmatrix} L^4 & -L^4 & 0 & 0 \\ \frac{\sigma_\epsilon}{\sigma_s} & \frac{\sigma_\nu}{\sigma_s} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The impulse response functions of the identified news and noise shocks are presented in figure 9. The method is successful in limiting the response of output per worker to noise. Both the job-finding rate and employment respond much stronger to the identified news than to the identified noise shocks. However, the response of the signal and therefore also the response of the job-finding rate and employment go in the wrong direction, as the response would be expected to be positive in both cases. This suggests a possible problem with the structural model imposed to identify news and noise shocks. It seems that the model is overcorrecting the response to noise, which then leads to the negative impulse response functions. A reason for this could be that the assumption that news and noise shocks are uncorrelated is too strong. Another more worrying problem could be that the series used to proxy for the signal actually does not contain enough information to correctly recover news and noise shocks, which would mean that the supposedly fundamental representation in equation 47 is non-fundamental.

**Figure 8:** Impulse responses to a 1% standard deviation shock $\epsilon_t$ (blue), $v_t$(black)




Nevertheless, the result of this simple VAR analysis suggests 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.

**Table 5:** Variance decomposition of the job-finding and employment rate due to News/Noise

| Quarters Ahead | 2 | 4 | 8 | 12 |
|---|---|---|---|---|
| job-finding rate | 89.9/10.1 % | 91.98/ 8.02% | 94.18/5.82 % | 95.21/4.79 % |
| Employment rate | 94.45/5.55% | 96.55/3.52 % | 98.19/1.81 % | 98.79/1.21% |

# 6 Limitations and possible extensions to the analysis

This paper should be viewed as a first exploration into the question of whether agents' erroneous expectations over the expected product of a job are an important factor in changes in job creation. It proposes two ways to tackle this complex question, but it cannot answer the question conclusively. There are important limitations to both the DSGE and the VAR model and the purpose of this section is to point out these limitations and to propose extensions to the presented models to address them.

As the maximum likelihood estimation is conditional on the model replicating labour market dynamics in response to the shocks reasonably well, the calibration and the modelling choices can be questioned. In general, the chosen parameters for the calibration are fairly conventional (see, for instance, 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) and lower matching elasticities need a different calibration to match labour market dynamics data well. In particular, in the model the combination of a high inter-temporal elasticity of substitution (parameter $\sigma$) and a low outside value to employment (parameter $b$), may turn the impulse response to noise upside down as wealth effects will then dominate the reaction to expectations shifts and firms will tend to postpone hiring to the time when the productivity increase is realized rather than spending the resources to find a worker in the periods following the noise shock. On the other hand, relaxing the Hosios condition in the direction that there is an inefficiently low number of vacancy postings as is assumed in Den Haan and Kaltenbrunner (2009) in order to match US data, will result in a stronger labour market response to noise shocks

and may even increase consumption. A straightforward extension to this analysis is thus to test the robustness of the results under a rage of different plausible calibrations of the search and matching model.

Concerning the modelling choices, a useful extension would be to nest the model in a broader framework encompassing an optimal capital choice going into production. Such a framework would probably render productivity shocks and expected productivity changes even more persistent as Den Haan, Ramey, and Watson (2000) suggests. Extending the model in this direction could also reduce the doubts about output per worker being a good proxy for productivity, which were mentioned in 4.1. As the optimal capital choice will be explicitly modelled in this case, changes due to noise or news in the capital per worker going into production would be accounted for. Another way to test the robustness of the choice of the productivity series would be to find other series which could act as proxies for productivity. Potential candidates would be real wages and firm profits, but also measures of total factor productivity. It could also be worth considering to relax the assumption that agents forecast perfectly rationally given the information they receive as the Kalman filter is a complex tool, which may not be accessible to the representative agent of the economy. Instead one could extend the model by implementing behavioural rules, such as the simple forecast rules with adaptive learning suggested in De Grauwe and Ji (2018). Finally, one could question the assumption that the representative worker and representative firm manager are equally well informed about future productivity developments. This restriction could be relaxed in the direction of higher noise affecting the signal extraction problem of the worker. Estimation of the two noise parameters would then have to rely on real wage or firm profit series.

The structural VAR model clearly produces dissatisfactory results. Given the imposed structure in section 5.1 one would expect that the effects of noise and news would affect the labour market in the same direction. The estimated impulse response functions of the recovered shocks seem to point to a different structure,

where the wealth effect dominates in response to noise and news and present productivity shocks are positively correlated. Thus a natural extension of the structural VAR model would be to impose a more general structure regarding the productivity process and the information contained in the signal. This could be, for instance of the form $\Delta p_t = \sum_{i=1}^{S} \phi_{1+i} L^i \epsilon_t$, where $\phi$ is some parameter. Another more basic worry is that the variable used to proxy for the signal may not contain enough information to identify the structural shocks. The MA representation, which is posited to be fundamental in the analysis above, may then actually not be fundamental. An extension to address this problem would be to broaden the set of potential instruments and conduct a FAVAR analysis similar to Forni, Gambetti, and Sala (2014). Finally, the VAR analysis may be affected by the same data problems for the measure of worker productivity discussed above for the estimation of the DSGE. For this reason it would also be good to repeat the estimation with different productivity series. For instance, using the series for potential output [GDPPOT] per worker, which is used in Forni et. al. (2017), the impulse responses of the recovered shocks turn around with the identified noise shock leading to increases in employment in the short run and the news shock leading to decreases.

# 7 Conclusion

This paper finds that noise is unlikely to play a significant role in hiring decisions and job creation in the US labour market. On the aggregate, firms and workers seem to be well informed about the present discounted value of a job match by observing current productivity, as signals on future innovations in aggregate worker productivity seem to largely contain news. While the model estimations should not be seen as providing conclusive evidence that there is no aggregate noise affecting the labour market, and a further investigation and extension to the presented analysis is necessary to achieve a comfortable degree of certainty, these preliminary results raise some interesting questions. Notwithstanding the results in Barsky and Sims (2012), who find that innovations in consumer confidence are almost exclusively due to news shocks and not due to noise shocks, a number of papers re-

cently have found evidence that a substantial portion of aggregate consumption fluctuations in the short run may be driven by noise (e.g. Blanchard, l'Huillier, and Lorenzoni, 2013, Forni et. al 2017).

If labour market decision-making is largely unaffected by noise, the question arises where these consumption fluctuations are mirrored on the production side. One possible explanation could be that noise affects the interest rate and the optimal choice of capital and investment, rather than the choice on labour input into production. Therefore extending the presented models by including an optimal capital choice for each worker, as suggested in section 6 may be a promising avenue for future research.

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# 8 Appendix

## 8.1 Dynare Code for the DSGE model

### 8.1.1 Model file

```
close all;

var n, v, u, c, theta, I, wage, Output,
n1,n2,n3,n4,n5,n6,n7,n8,n9,n10,n11,n12,n13,n14,n15
v1,v2,v3,v4,v5,v6,v7,v8,v9,v10,v11,v12,v13,v14,v15
u1,u2,u3,u4,u5,u6,u7,u8,u9,u10,u11,u12,u13,u14,u15
c1,c2,c3,c4,c5,c6,c7,c8,c9,c10,c11,c12,c13,c14,c15
t1,t2,t3,t4,t5,t6,t7,t8,t9,t10,t11,t12,t13,t14,t15
a,a1,a2,a3,a4,a5,a6,a7,a8,a9,a10,a11,a12,a13,a14,a15,aLR,
Da,Dn, Du, DJobfindingrate, DUnemployment, DLYpN,DLYPotpL, Consumption
IKFA11,IKFA12,IKFA13,IKFA21,IKFA22,IKFA23,IKFA31,IKFA32,IKFA33,K11,K12,K21,K22,K31,K32
dx x z s prod dprod xtt xt1t ztt dcons Unemployment Jobfindingrate;


varexo eta epsilon nu;

parameters beda, sigma,lmb,xi,pis,kap, b, m,
rho sig_u sig_nu;

m=0.77;
beda=0.99;
sigma=1;
lmb=0.25;
xi= 0.7;
pis=1-xi;
kap=0.0365;
```

```
b=0.8825;
rho = 0.9;
sig_u = 0.006;
sig_nu = 0.0006;

model;

/*IKFA-- K-- are actually the values of the agent Kalman filter-
these are estimated in the steady state file from the parameters rho, sig_u, and sig_nu */
IKFA11=IKFA11(-1);
IKFA12=IKFA12(-1);
IKFA13=IKFA13(-1);
IKFA21=IKFA21(-1);
IKFA22=IKFA22(-1);
IKFA23=IKFA23(-1);
IKFA31=IKFA31(-1);
IKFA32=IKFA32(-1);
IKFA33=IKFA33(-1);
K11=K11(-1);
K21=K21(-1);
K31=K31(-1);
K12=K12(-1);
K22=K22(-1);
K32=K32(-1);

/*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= pis*(a-b)+(1-lmb)*beda*(c^sigma/ c1^sigma)*(kap *t1^xi/m - (1-pis) * kap*t1);
c= n*a -kap*v+b*(1-n);
I=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)*(1+rho)-rho*xt1t(-1)+rho*ztt(-1);
a1=(a-rho*ztt(-1))*(1+rho)-rho*xtt(-1)+rho^2*ztt(-1);
a2=(a1-rho^2*ztt(-1))*(1+rho)-rho*(a-rho*ztt(-1))+rho^3*ztt(-1);
a3=(a2-rho^3*ztt(-1))*(1+rho)-rho*(a1-rho^2*ztt(-1))+rho^4*ztt(-1);
```

```
a4=(a3-rho^4*ztt(-1))*(1+rho)-rho*(a2-rho^3*ztt(-1))+rho^5*ztt(-1);
a5=(a4-rho^5*ztt(-1))*(1+rho)-rho*(a3-rho^4*ztt(-1))+rho^6*ztt(-1);
a6=(a5-rho^6*ztt(-1))*(1+rho)-rho*(a4-rho^5*ztt(-1))+rho^7*ztt(-1);
a7=(a6-rho^7*ztt(-1))*(1+rho)-rho*(a5-rho^6*ztt(-1))+rho^8*ztt(-1);
a8=(a7-rho^8*ztt(-1))*(1+rho)-rho*(a6-rho^7*ztt(-1))+rho^9*ztt(-1);
a9=(a8-rho^9*ztt(-1))*(1+rho)-rho*(a7-rho^8*ztt(-1))+rho^10*ztt(-1);
a10=(a9-rho^10*ztt(-1))*(1+rho)-rho*(a8-rho^9*ztt(-1))+rho^11*ztt(-1);
a11=(a10-rho^11*ztt(-1))*(1+rho)-rho*(a9-rho^10*ztt(-1))+rho^12*ztt(-1);
a12=(a11-rho^12*ztt(-1))*(1+rho)-rho*(a10-rho^11*ztt(-1))+rho^13*ztt(-1);
a13=(a12-rho^13*ztt(-1))*(1+rho)-rho*(a11-rho^12*ztt(-1))+rho^14*ztt(-1);
a14=(a13-rho^14*ztt(-1))*(1+rho)-rho*(a12-rho^13*ztt(-1))+rho^15*ztt(-1);
a15=(a14-rho^15*ztt(-1))*(1+rho)-rho*(a13-rho^14*ztt(-1))+rho^16*ztt(-1);
aLR = xtt(-1) + (xtt(-1)-xt1t(-1))*(rho/(1-rho));
Da=aLR-a15;
/*Technically, this iteration, as the iteration of the other expected variables
should continue to infinity. However, due to the decreasingly
small difference in the between the impact of the shock on a15 and aLR
(expected long run productivity after infinite periods),
a reasonable estimation can be achieved by only including
the next 15 periods in the forward iterations of the agents expectations. */


/*Expected employment*/
n1= (1-lmb)*n+m*v1^(1-xi)*u1^xi;
n2= (1-lmb)*n1+m*v2^(1-xi)*u2^xi;
n3= (1-lmb)*n2+m*v3^(1-xi)*u3^xi;
n4= (1-lmb)*n3+m*v4^(1-xi)*u4^xi;
n5= (1-lmb)*n4+m*v5^(1-xi)*u5^xi;
n6= (1-lmb)*n5+m*v6^(1-xi)*u6^xi;
n7= (1-lmb)*n6+m*v7^(1-xi)*u7^xi;
n8= (1-lmb)*n7+m*v8^(1-xi)*u8^xi;
n9= (1-lmb)*n8+m*v9^(1-xi)*u9^xi;
n10= (1-lmb)*n9+m*v10^(1-xi)*u10^xi;
n11= (1-lmb)*n10+m*v11^(1-xi)*u11^xi;
n12= (1-lmb)*n11+m*v12^(1-xi)*u12^xi;
n13= (1-lmb)*n12+m*v13^(1-xi)*u13^xi;
n14= (1-lmb)*n13+m*v14^(1-xi)*u14^xi;
n15= (1-lmb)*n14+m*v15^(1-xi)*u15^xi;


/*Expected pre-matching unemployment*/
u1=1-(1-lmb)*n;
u2=1-(1-lmb)*n1;
u3=1-(1-lmb)*n2;
u4=1-(1-lmb)*n3;
u5=1-(1-lmb)*n4;
u6=1-(1-lmb)*n5;
u7=1-(1-lmb)*n6;
u8=1-(1-lmb)*n7;
u9=1-(1-lmb)*n8;
u10=1-(1-lmb)*n9;
u11=1-(1-lmb)*n10;
u12=1-(1-lmb)*n11;
u13=1-(1-lmb)*n12;
u14=1-(1-lmb)*n13;
u15=1-(1-lmb)*n14;

/*Expected theta*/
```

```
t1=v1/u1;
t2=v2/u2;
t3=v3/u3;
t4=v4/u4;
t5=v5/u5;
t6=v6/u6;
t7=v7/u7;
t8=v8/u8;
t9=v9/u9;
t10=v10/u10;
t11=v11/u11;
t12=v12/u12;
t13=v13/u13;
t14=v14/u14;
t15=v15/u15;


/*Expected Job creation*/
t1^xi*kap/m= pis*(a1-b)+(1-lmb)*beda*(c1^sigma/ c2^sigma)*(kap *t2^xi/m - (1-pis) * kap*t2);
t2^xi*kap/m= pis*(a2-b)+(1-lmb)*beda*(c2^sigma/ c3^sigma)*(kap *t3^xi/m - (1-pis) * kap*t3);
t3^xi*kap/m= pis*(a3-b)+(1-lmb)*beda*(c3^sigma/ c4^sigma)*(kap *t4^xi/m - (1-pis) * kap*t4);
t4^xi*kap/m= pis*(a4-b)+(1-lmb)*beda*(c4^sigma/ c5^sigma)*(kap *t5^xi/m - (1-pis) * kap*t5);
t5^xi*kap/m= pis*(a5-b)+(1-lmb)*beda*(c5^sigma/ c6^sigma)*(kap *t6^xi/m - (1-pis) * kap*t6);
t6^xi*kap/m= pis*(a6-b)+(1-lmb)*beda*(c6^sigma/ c7^sigma)*(kap *t7^xi/m - (1-pis) * kap*t7);
t7^xi*kap/m= pis*(a7-b)+(1-lmb)*beda*(c7^sigma/ c8^sigma)*(kap *t8^xi/m - (1-pis) * kap*t8);
t8^xi*kap/m= pis*(a8-b)+(1-lmb)*beda*(c8^sigma/ c9^sigma)*(kap *t9^xi/m - (1-pis) * kap*t9);
t9^xi*kap/m= pis*(a9-b)+(1-lmb)*beda*(c9^sigma/ c10^sigma)*(kap *t10^xi/m - (1-pis) * kap*t10);
t10^xi*kap/m= pis*(a10-b)+(1-lmb)*beda*(c10^sigma/ c11^sigma)*(kap *t11^xi/m - (1-pis) * kap*t11);
t11^xi*kap/m= pis*(a11-b)+(1-lmb)*beda*(c11^sigma/ c12^sigma)*(kap *t12^xi/m - (1-pis) * kap*t12);
t12^xi*kap/m= pis*(a12-b)+(1-lmb)*beda*(c12^sigma/ c13^sigma)*(kap *t13^xi/m - (1-pis) * kap*t13);
t13^xi*kap/m= pis*(a13-b)+(1-lmb)*beda*(c13^sigma/ c14^sigma)*(kap *t14^xi/m - (1-pis) * kap*t14);
t14^xi*kap/m= pis*(a14-b)+(1-lmb)*beda*(c14^sigma/ c15^sigma)*(kap *t15^xi/m - (1-pis) * kap*t15);
t15^xi*kap/m= pis*(a15-b)+(1-lmb)*beda*(c15^sigma/ c15(+1)^sigma)*
(kap*t15(+1)^xi/m - (1-pis) * kap*t15(+1));

/*Expected Consumption*/
c1= n1* a1 -kap*v1+b*(1-n1);
c2= n2* a2 -kap*v2+b*(1-n2);
c3= n3* a3 -kap*v3+b*(1-n3);
c4= n4* a4 -kap*v4+b*(1-n4);
c5= n5* a5 -kap*v5+b*(1-n5);
c6= n6* a6 -kap*v6+b*(1-n6);
c7= n7* a7 -kap*v7+b*(1-n7);
c8= n8* a8 -kap*v8+b*(1-n8);
c9= n9* a9 -kap*v9+b*(1-n9);
c10= n10*a10-kap*v10+b*(1-n10);
c11= n11*a11-kap*v11+b*(1-n11);
c12= n12*a12-kap*v12+b*(1-n12);
c13= n13*a13-kap*v13+b*(1-n13);
c14= n14*a14-kap*v14+b*(1-n14);
c15= n15*a15-kap*v15+b*(1-n15);

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

```
Du=u-u(-1);
DJobfindingrate=Jobfindingrate-Jobfindingrate(-1);
DUnemployment=Unemployment-Unemployment(-1);
DLYpN=dprod;
DLYPotpL=dprod;

end;

steady;

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


estimated_params;
rho, 0.9,0,1;
sig_u, 0.06,0, 1;
sig_nu, 0.0004,0, 1;
end;
varobs DLYpN DJobfindingrate;
estimation(datafile=Estimation_data,prefilter=1,lik_init=2,first_obs=1);

model_diagnostics;

stoch_simul(irf = 40, order =1) Output Consumption  n I Jobfindingrate  DJobfindingrate Dn;
```

### 8.1.2 Steady state file

```
function [ys,check] = FOC_model_steadystate(ys,exe)
global M_

%% Here we load the values of the deep parameters in a loop.
NumberOfParameters = M_.param_nbr;                          % Number of deep
    parameters.
for i = 1:NumberOfParameters                                % Loop...
  paramname = deblank(M_.param_names(i,:));                  %    Get the name of
       parameter i.
  eval([ paramname ' = M_.params(' int2str(i) ');']);       %    Get the value
      of parameter i.
end                                                         % End of the loop.
check = 0;
%% END OF THE FIRST MODEL INDEPENDENT BLOCK.
%% THIS BLOCK IS MODEL SPECIFIC.

%Finding the labour market steady state
y0=[2,0.5];
[y,fval]=fsolve(@(y) [ (pis*(1- b)- kap /m *(1-beda*(1-lmb))* y(1)^xi)/(kap*beda
    *(1-lmb)*(1-pis))-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);
I=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;
xtt=1; xt1t=1; ztt=0;

%Steady states of the agent's expected path of the endogenous variables
n1=n; n2=n; n3=n; n4=n; n5=n; n6=n; n7=n; n8=n; n9=n; n10=n; n11=n; n12=n; n13=n;
    n14=n; n15=n;
u1=u; u2=u; u3=u; u4=u; u5=u; u6=u; u7=u; u8=u; u9=u; u10=u; u11=u; u12=u; u13=u;
    u14=u; u15=u;
v1=v; v2=v; v3=v; v4=v; v5=v; v6=v; v7=v; v8=v; v9=v; v10=v; v11=v; v12=v; v13=v;
    v14=v; v15=v;
c1=c; c2=c; c3=c; c4=c; c5=c; c6=c; c7=c; c8=c; c9=c; c10=c; c11=c; c12=c; c13=c;
    c14=c; c15=c;
t1=theta; t2=theta; t3=theta; t4=theta; t5=theta; t6=theta; t7=theta; t8=theta; t9
    =theta; t10=theta; t11=theta; t12=theta; t13=theta; t14=theta; t15=theta;
a=1; a1=1; a2=1; a3=1; a4=1; a5=1; a6=1; a7=1; a8=1; a9=1; a10=1; a11=1; a12=1;
    a13=1; a14=1; a15=1; aLR=1; Da=0;

%Steady states for other variables of interest
wage=b*pis+(1-pis)*(a+beda*(1-lmb)*c/c1*kap*t1); Consumption=c; Dn=0; Du=0;
    DJobfindingrate=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);

%% Here we define the steady state values of the endogenous variables of the model
    .
NumberOfEndogenousVariables = M_.endo_nbr;                    % Number of
    endogenous variables.
ys = zeros(NumberOfEndogenousVariables,1);                    % Initialization of
    ys (steady state).
for i = 1:NumberOfEndogenousVariables                         % Loop...
  varname = deblank(M_.endo_names(i,:));                      %     Get the name of
      endogenous variable i.
```

```
  eval(['ys(' int2str(i) ') = ' varname ';']);                    %    Get the steady
      state value of this variable.
end                                                               % End of the loop.
%% END OF THE SECOND MODEL INDEPENDENT BLOCK.
```

## 8.2 VAR code

```
clear
%%% Loading and transforming the relevant Time Series
load('VAR_data.mat')
B12=str2double(Vardata.B12);
B12=B12/mean(B12)-1;
DP=Vardata.DLYpN;
DP=DP-mean(DP);
JobF=Vardata.Jobfindingrate-mean(Vardata.Jobfindingrate);
N=1-Vardata.Unemployment;
N=N-mean(N);

%Parameter S defininig assumed lag of signal/news
Backward=4;

%Unrestricted VAR estimation
Varmod=varm(4,1);
Varmod.Constant=[0,0,0,0]';
EstMdl = estimate(Varmod,[DP B12 JobF N])
summarize(EstMdl)
EstMat=EstMdl.AR{1}
Residuals = infer(EstMdl,[DP B12 JobF N]);

%Estimates of news/noise over signal variance
B=EstMat^Backward;
Estsigesigs=sin(atan(B(1,2)/B(1,1)));
Estsigvsigs=cos(atan(B(1,2)/B(1,1)));

%Recovering strucutral shocks
U=Residuals(:,1);
S=Residuals(:,2);
E1=Residuals(:,3);
E2=Residuals(:,4);
Structurale=zeros(1,232)
Structuralv=zeros(1,232)
x=5
while x<232
Structurale(x-4)=U(x)+ S(x-4)*Estsigesigs^2
Structuralv(x-4)=-U(x) + S(x-4)*Estsigvsigs^2
x=x+1;
end

%Generating unrestricted IRF
x=0:40


Shock=[0,0.01*sqrt(var(Residuals(:,2))),0,0]'
IRFSS=zeros(41,4)'
IRFSS(:,1)=Shock
for i=1:40
    IRFSS(:,i+1)=EstMat^i*Shock
end
```

```
Shock=[0.01*sqrt(var(Residuals(:,1))),0,0,0]'
IRFSE=zeros(41,4)'
IRFSE(:,1)=Shock
for i=1:40
    IRFSE(:,i+1)=EstMat^i*Shock
end

Shock=[0,0,0.01*sqrt(var(Residuals(:,3))),0]'
IRFSX1=zeros(41,4)'
IRFSX1(:,1)=Shock
for i=1:40
    IRFSX1(:,i+1)=EstMat^i*Shock
end

Shock=[0,0,0,0.01*sqrt(var(Residuals(:,4)))]'
IRFSX2=zeros(41,4)'
IRFSX2(:,1)=Shock
for i=1:40
    IRFSX2(:,i+1)=EstMat^i*Shock
end

h=figure
subplot(2,2,1)
plot(x,IRFSE(1,:),'-b',x,IRFSS(1,:),'-k',x,IRFSX1(1,:),'--m',x,IRFSX2(1,:),'--r')
title('Output per Worker')
xlabel('Quarters')

subplot(2,2,2)
plot(x,IRFSE(2,:),'-b',x,IRFSS(2,:),'-k',x,IRFSX1(2,:),'--m',x,IRFSX2(2,:),'--r')
title('Signal Instrument')
xlabel('Quarters')

subplot(2,2,3)
plot(x,IRFSE(3,:),'-b',x,IRFSS(3,:),'-k',x,IRFSX1(3,:),'--m',x,IRFSX2(3,:),'--r')
title('Jobfinding rate')
xlabel('Quarters')

subplot(2,2,4)
plot(x,IRFSE(4,:),'-b',x,IRFSS(4,:),'-k',x,IRFSX1(4,:),'--m',x,IRFSX2(4,:),'--r')
title('Employment')
xlabel('Quarters')

set(h,'Units','Inches');
pos = get(h,'Position');
orient(h,'landscape')
print(h,'VarShocks','-dpdf','-fillpage')

%Generating IRF of "structural" shocks

Shock=[0.01*sqrt(var(Structurale)),0,0,0]'
IRFS=zeros(31,4)'

for i=1:30
    A=EstMat^(i)
    B=EstMat^(i+Backward)
    A(1,1)=B(1,1)*Estsigvsigs+Estsigesigs*A(1,2)
    A(2,1)=B(2,1)*Estsigvsigs+Estsigesigs*A(2,2)
```

```
    A(3,1)=B(3,1)*Estsigvsigs+Estsigesigs*A(3,2)
    A(4,1)=B(4,1)*Estsigvsigs+Estsigesigs*A(4,2)
    A(1,2)=-B(1,1)*Estsigesigs+Estsigvsigs*A(1,2)
    A(2,2)=-B(2,1)*Estsigesigs+Estsigvsigs*A(2,2)
    A(3,2)=-B(3,1)*Estsigesigs+Estsigvsigs*A(3,2)
    A(4,2)=-B(4,1)*Estsigesigs+Estsigvsigs*A(4,2)
   IRFS(:,i+1)=A*Shock
end


Shock=[0,0.01*sqrt(var(Structuralv)),0,0]'
IRFS2=zeros(31,4)'
for i=1:30
    A=EstMat^(i)
    B=EstMat^(i+Backward)
    A(1,1)=B(1,1)*Estsigvsigs+Estsigesigs*A(1,2)
    A(2,1)=B(2,1)*Estsigvsigs+Estsigesigs*A(2,2)
    A(3,1)=B(3,1)*Estsigvsigs+Estsigesigs*A(3,2)
    A(4,1)=B(4,1)*Estsigvsigs+Estsigesigs*A(4,2)
    A(1,2)=-B(1,1)*Estsigesigs+Estsigvsigs*A(1,2)
    A(2,2)=-B(2,1)*Estsigesigs+Estsigvsigs*A(2,2)
    A(3,2)=-B(3,1)*Estsigesigs+Estsigvsigs*A(3,2)
    A(4,2)=-B(4,1)*Estsigesigs+Estsigvsigs*A(4,2)
   IRFS2(:,i+1)=A*Shock
end



x=0:30
Struct=figure
subplot(2,2,1)
plot(x,IRFS(1,:),'-b',x,IRFS2(1,:),'-k')
title('(Expected) Output per Worker')
xlabel('Quarters')

subplot(2,2,2)
plot(x,IRFS(2,:),'-b',x,IRFS2(2,:),'-k')
title('Signal Instrument')
xlabel('Quarters')

subplot(2,2,3)
plot(x,IRFS(3,:),'-b',x,IRFS2(3,:),'-k')
title('Jobfinding rate')
xlabel('Quarters')

subplot(2,2,4)
plot(x,IRFS(4,:),'-b',x,IRFS2(4,:),'-k')
title('Employment')
xlabel('Quarters')

set(Struct,'Units','Inches');
pos = get(Struct,'Position');
orient(Struct,'landscape')
print(Struct,'StructShocks','-dpdf','-fillpage')
```

## 8.3 Quarterly data series

| Time | Difference of log of Real Output per Worker (coded as ""DLYpN"") | | | | Jobfindingrate | |
|---|---|---|---|---|---|---|
| Unemployment | DJobfindingrate | | DUnemployment | Expected Business Conditions in 12 months | | |
| 1949.50 | 0.0079 | 0.8373 | 0.0593 | -0.0597 | 0.0123 | - |
| 1949.75 | 0.0127 | 0.8162 | 0.0676 | -0.0211 | 0.0083 | - |
| 1950.00 | -0.0145 | 0.8756 | 0.0704 | 0.0594 | 0.0028 | - |
| 1950.25 | 0.0391 | 0.8323 | 0.0647 | -0.0433 | -0.0057 | - |
| 1950.50 | 0.0116 | 0.8674 | 0.0563 | 0.0351 | -0.0084 | - |
| 1950.75 | 0.0260 | 0.8913 | 0.0471 | 0.0239 | -0.0091 | - |
| 1951.00 | 0.0160 | 0.9254 | 0.0427 | 0.0341 | -0.0044 | - |
| 1951.25 | 0.0093 | 0.9548 | 0.0358 | 0.0294 | -0.0069 | - |
| 1951.50 | 0.0172 | 0.9534 | 0.0318 | -0.0014 | -0.0040 | - |
| 1951.75 | 0.0195 | 0.9541 | 0.0327 | 0.0007 | 0.0009 | - |
| 1952.00 | -0.0005 | 0.9469 | 0.0346 | -0.0071 | 0.0019 | - |
| 1952.25 | 0.0078 | 0.9725 | 0.0314 | 0.0256 | -0.0032 | - |
| 1952.50 | 0.0049 | 0.9626 | 0.0306 | -0.0100 | -0.0009 | - |
| 1952.75 | 0.0074 | 0.9575 | 0.0330 | -0.0051 | 0.0024 | - |
| 1953.00 | 0.0237 | 0.9561 | 0.0287 | -0.0014 | -0.0042 | - |
| 1953.25 | -0.0015 | 0.9801 | 0.0275 | 0.0241 | -0.0012 | - |
| 1953.50 | 0.0163 | 0.9644 | 0.0268 | -0.0158 | -0.0008 | - |
| 1953.75 | -0.0031 | 0.9657 | 0.0280 | 0.0013 | 0.0012 | - |
| 1954.00 | -0.0052 | 0.9097 | 0.0378 | -0.0560 | 0.0098 | - |
| 1954.25 | -0.0006 | 0.8550 | 0.0531 | -0.0547 | 0.0153 | - |
| 1954.50 | 0.0065 | 0.8515 | 0.0586 | -0.0035 | 0.0055 | - |
| 1954.75 | 0.0119 | 0.8226 | 0.0605 | -0.0289 | 0.0019 | - |
| 1955.00 | 0.0139 | 0.8691 | 0.0544 | 0.0466 | -0.0061 | - |
| 1955.25 | 0.0188 | 0.8367 | 0.0479 | -0.0324 | -0.0065 | - |
| 1955.50 | 0.0026 | 0.9011 | 0.0446 | 0.0644 | -0.0033 | - |
| 1955.75 | -0.0045 | 0.8958 | 0.0419 | -0.0053 | -0.0027 | - |
| 1956.00 | -0.0028 | 0.9006 | 0.0429 | 0.0048 | 0.0010 | - |
| 1956.25 | -0.0078 | 0.9098 | 0.0411 | 0.0092 | -0.0018 | - |
| 1956.50 | 0.0050 | 0.8933 | 0.0427 | -0.0165 | 0.0016 | - |
| 1956.75 | -0.0037 | 0.9211 | 0.0421 | 0.0278 | -0.0006 | - |
| 1957.00 | 0.0171 | 0.8935 | 0.0418 | -0.0276 | -0.0003 | - |
| 1957.25 | 0.0032 | 0.9062 | 0.0403 | 0.0127 | -0.0015 | - |
| 1957.50 | -0.0019 | 0.8882 | 0.0414 | -0.0180 | 0.0011 | - |
| 1957.75 | 0.0077 | 0.8806 | 0.0429 | -0.0076 | 0.0014 | - |
| 1958.00 | -0.0052 | 0.8116 | 0.0500 | -0.0690 | 0.0072 | - |
| 1958.25 | -0.0116 | 0.7629 | 0.0635 | -0.0488 | 0.0135 | - |
| 1958.50 | 0.0098 | 0.7577 | 0.0744 | -0.0052 | 0.0109 | - |
| 1958.75 | 0.0191 | 0.7739 | 0.0739 | 0.0163 | -0.0005 | - |
| 1959.00 | 0.0149 | 0.8156 | 0.0643 | 0.0417 | -0.0096 | - |
| 1959.25 | 0.0115 | 0.8308 | 0.0588 | 0.0152 | -0.0055 | - |
| 1959.50 | 0.0111 | 0.8487 | 0.0518 | 0.0179 | -0.0069 | - |
| 1959.75 | -0.0035 | 0.8275 | 0.0537 | -0.0212 | 0.0018 | - |
| 1960.00 | 0.0031 | 0.8662 | 0.0567 | 0.0387 | 0.0031 | 168 |
| 1960.25 | 0.0176 | 0.8577 | 0.0524 | -0.0085 | -0.0043 | 154 |
| 1960.50 | -0.0167 | 0.8580 | 0.0530 | 0.0003 | 0.0007 | 152 |
| 1960.75 | 0.0031 | 0.8168 | 0.0563 | -0.0412 | 0.0032 | 142 |
| 1961.00 | -0.0094 | 0.8067 | 0.0633 | -0.0101 | 0.0070 | 135 |
| 1961.25 | 0.0083 | 0.7807 | 0.0685 | -0.0260 | 0.0052 | 147 |
| 1961.50 | 0.0204 | 0.7620 | 0.0705 | -0.0187 | 0.0020 | 156 |
| 1961.75 | 0.0156 | 0.8071 | 0.0683 | 0.0451 | -0.0022 | 148 |
| 1962.00 | 0.0155 | 0.8338 | 0.0625 | 0.0267 | -0.0058 | 163 |
| 1962.25 | 0.0116 | 0.8307 | 0.0569 | -0.0031 | -0.0056 | 153 |
| 1962.50 | 0.0078 | 0.8220 | 0.0556 | -0.0086 | -0.0013 | 142 |
| 1962.75 | 0.0049 | 0.8419 | 0.0562 | 0.0199 | 0.0006 | 154 |
| 1963.00 | 0.0026 | 0.8357 | 0.0559 | -0.0062 | -0.0003 | 156 |
| 1963.25 | 0.0084 | 0.8344 | 0.0586 | -0.0013 | 0.0027 | 145 |
| 1963.50 | 0.0057 | 0.8383 | 0.0576 | 0.0039 | -0.0010 | 152 |
| 1963.75 | 0.0140 | 0.8420 | 0.0557 | 0.0036 | -0.0019 | 156 |
| 1964.00 | 0.0033 | 0.8515 | 0.0565 | 0.0096 | 0.0008 | 162 |
| 1964.25 | 0.0162 | 0.8564 | 0.0554 | 0.0049 | -0.0011 | 159 |
| 1964.50 | 0.0004 | 0.8574 | 0.0530 | 0.0010 | -0.0024 | 155 |
| 1964.75 | 0.0124 | 0.8635 | 0.0507 | 0.0061 | -0.0023 | 168 |
| 1965.00 | 0.0002 | 0.8662 | 0.0503 | 0.0027 | -0.0004 | 168 |
| 1965.25 | 0.0175 | 0.8801 | 0.0495 | 0.0139 | -0.0008 | 159 |
| 1965.50 | 0.0035 | 0.9019 | 0.0473 | 0.0218 | -0.0022 | 158 |
| 1965.75 | 0.0135 | 0.9005 | 0.0443 | -0.0013 | -0.0030 | 163 |
| 1966.00 | 0.0169 | 0.8990 | 0.0418 | -0.0016 | -0.0025 | 160 |
| 1966.25 | 0.0196 | 0.9288 | 0.0393 | 0.0298 | -0.0025 | 153 |
| 1966.50 | -0.0017 | 0.9387 | 0.0389 | 0.0099 | -0.0004 | 142 |
| 1966.75 | 0.0003 | 0.9365 | 0.0383 | -0.0022 | -0.0006 | 139 |
| 1967.00 | 0.0008 | 0.9202 | 0.0376 | -0.0163 | -0.0007 | 147 |
| 1967.25 | 0.0103 | 0.9294 | 0.0389 | 0.0092 | 0.0013 | 146 |
| 1967.50 | -0.0049 | 0.9330 | 0.0389 | 0.0036 | 0.0000 | 150 |
| 1967.75 | -0.0010 | 0.9261 | 0.0386 | -0.0069 | -0.0002 | 142 |
| 1968.00 | 0.0013 | 0.9272 | 0.0400 | 0.0011 | 0.0013 | 141 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1968.25 | 0.0216 | 0.9410 | 0.0381 | 0.0138 | -0.0019 | 140 |
| 1968.50 | 0.0055 | 0.9434 | 0.0362 | 0.0024 | -0.0019 | 134 |
| 1968.75 | 0.0052 | 0.9507 | 0.0359 | 0.0073 | -0.0003 | 142 |
| 1969.00 | -0.0008 | 0.9449 | 0.0347 | -0.0058 | -0.0012 | 152 |
| 1969.25 | 0.0067 | 0.9412 | 0.0346 | -0.0037 | -0.0002 | 141 |
| 1969.50 | -0.0025 | 0.9533 | 0.0350 | 0.0121 | 0.0005 | 135 |
| 1969.75 | -0.0008 | 0.9406 | 0.0367 | -0.0127 | 0.0017 | 112 |
| 1970.00 | -0.0098 | 0.9296 | 0.0366 | -0.0110 | -0.0001 | 105 |
| 1970.25 | -0.0044 | 0.9193 | 0.0424 | -0.0103 | 0.0058 | 93 |
| 1970.50 | 0.0036 | 0.9018 | 0.0483 | -0.0175 | 0.0059 | 105 |
| 1970.75 | 0.0091 | 0.8938 | 0.0525 | -0.0080 | 0.0042 | 98 |
| 1971.00 | -0.0107 | 0.8591 | 0.0588 | -0.0347 | 0.0063 | 105 |
| 1971.25 | 0.0255 | 0.8471 | 0.0599 | -0.0120 | 0.0011 | 110 |
| 1971.50 | 0.0026 | 0.8455 | 0.0599 | -0.0016 | -0.0001 | 117 |
| 1971.75 | 0.0008 | 0.8614 | 0.0606 | 0.0158 | 0.0008 | 109 |
| 1972.00 | -0.0061 | 0.8565 | 0.0603 | -0.0049 | -0.0003 | 137 |
| 1972.25 | 0.0056 | 0.8533 | 0.0586 | -0.0032 | -0.0017 | 118 |
| 1972.50 | 0.0148 | 0.8620 | 0.0575 | 0.0087 | -0.0011 | 140 |
| 1972.75 | 0.0022 | 0.8800 | 0.0568 | 0.0180 | -0.0007 | 129 |
| 1973.00 | 0.0098 | 0.8844 | 0.0540 | 0.0044 | -0.0028 | 99 |
| 1973.25 | 0.0143 | 0.8934 | 0.0504 | 0.0090 | -0.0035 | 85 |
| 1973.50 | -0.0001 | 0.9183 | 0.0498 | 0.0249 | -0.0006 | 76 |
| 1973.75 | -0.0117 | 0.9108 | 0.0489 | -0.0074 | -0.0010 | 78 |
| 1974.00 | -0.0013 | 0.8973 | 0.0486 | -0.0135 | -0.0002 | 45 |
| 1974.25 | -0.0138 | 0.9077 | 0.0518 | 0.0104 | 0.0032 | 75 |
| 1974.50 | 0.0012 | 0.8926 | 0.0525 | -0.0151 | 0.0008 | 64 |
| 1974.75 | -0.0126 | 0.8894 | 0.0568 | -0.0032 | 0.0042 | 46 |
| 1975.00 | 0.0016 | 0.8193 | 0.0665 | -0.0701 | 0.0097 | 46 |
| 1975.25 | 0.0022 | 0.7646 | 0.0831 | -0.0547 | 0.0166 | 92 |
| 1975.50 | 0.0080 | 0.7568 | 0.0892 | -0.0078 | 0.0061 | 97 |
| 1975.75 | 0.0070 | 0.7724 | 0.0856 | 0.0156 | -0.0036 | 93 |
| 1976.00 | 0.0092 | 0.7682 | 0.0835 | -0.0042 | -0.0021 | 119 |
| 1976.25 | 0.0087 | 0.7928 | 0.0781 | 0.0246 | -0.0054 | 119 |
| 1976.50 | -0.0027 | 0.7912 | 0.0762 | -0.0015 | -0.0020 | 128 |
| 1976.75 | -0.0014 | 0.7990 | 0.0779 | 0.0077 | 0.0017 | 118 |
| 1977.00 | 0.0029 | 0.7945 | 0.0782 | -0.0045 | 0.0003 | 117 |
| 1977.25 | 0.0028 | 0.8270 | 0.0758 | 0.0325 | -0.0024 | 122 |
| 1977.50 | 0.0051 | 0.8326 | 0.0719 | 0.0056 | -0.0039 | 117 |
| 1977.75 | 0.0094 | 0.8327 | 0.0695 | 0.0001 | -0.0024 | 106 |
| 1978.00 | -0.0131 | 0.8449 | 0.0670 | 0.0122 | -0.0025 | 103 |
| 1978.25 | -0.0062 | 0.8594 | 0.0639 | 0.0146 | -0.0031 | 98 |
| 1978.50 | 0.0247 | 0.8723 | 0.0606 | 0.0128 | -0.0033 | 92 |
| 1978.75 | 0.0039 | 0.8841 | 0.0608 | 0.0118 | 0.0002 | 78 |
| 1979.00 | 0.0030 | 0.8700 | 0.0595 | -0.0140 | -0.0014 | 70 |
| 1979.25 | -0.0067 | 0.8768 | 0.0594 | 0.0067 | -0.0001 | 58 |
| 1979.50 | 0.0000 | 0.8862 | 0.0578 | 0.0095 | -0.0016 | 48 |
| 1979.75 | 0.0004 | 0.8859 | 0.0593 | -0.0004 | 0.0015 | 50 |
| 1980.00 | -0.0034 | 0.8737 | 0.0600 | -0.0121 | 0.0007 | 51 |
| 1980.25 | 0.0010 | 0.8508 | 0.0636 | -0.0230 | 0.0036 | 35 |
| 1980.50 | -0.0113 | 0.8176 | 0.0738 | -0.0332 | 0.0103 | 64 |
| 1980.75 | -0.0010 | 0.8150 | 0.0774 | -0.0025 | 0.0036 | 81 |
| 1981.00 | 0.0123 | 0.8082 | 0.0746 | -0.0068 | -0.0028 | 70 |
| 1981.25 | 0.0131 | 0.8218 | 0.0749 | 0.0137 | 0.0003 | 89 |
| 1981.50 | -0.0129 | 0.8238 | 0.0746 | 0.0019 | -0.0003 | 84 |
| 1981.75 | 0.0146 | 0.8077 | 0.0748 | -0.0161 | 0.0002 | 59 |
| 1982.00 | -0.0077 | 0.8122 | 0.0830 | 0.0045 | 0.0082 | 55 |
| 1982.25 | -0.0132 | 0.7754 | 0.0890 | -0.0368 | 0.0060 | 61 |
| 1982.50 | 0.0051 | 0.7448 | 0.0949 | -0.0306 | 0.0058 | 64 |
| 1982.75 | -0.0016 | 0.7292 | 0.1000 | -0.0156 | 0.0052 | 77 |
| 1983.00 | 0.0052 | 0.7151 | 0.1074 | -0.0140 | 0.0073 | 91 |
| 1983.25 | 0.0128 | 0.7072 | 0.1046 | -0.0080 | -0.0028 | 131 |
| 1983.50 | 0.0145 | 0.7330 | 0.1016 | 0.0258 | -0.0029 | 130 |
| 1983.75 | 0.0029 | 0.7693 | 0.0942 | 0.0362 | -0.0074 | 131 |
| 1984.00 | 0.0108 | 0.7870 | 0.0860 | 0.0177 | -0.0082 | 146 |
| 1984.25 | 0.0092 | 0.7916 | 0.0793 | 0.0046 | -0.0067 | 132 |
| 1984.50 | 0.0042 | 0.8004 | 0.0754 | 0.0088 | -0.0039 | 137 |
| 1984.75 | 0.0067 | 0.8186 | 0.0751 | 0.0182 | -0.0003 | 132 |
| 1985.00 | 0.0024 | 0.8236 | 0.0734 | 0.0049 | -0.0017 | 133 |
| 1985.25 | 0.0036 | 0.8263 | 0.0734 | 0.0027 | 0.0000 | 127 |
| 1985.50 | 0.0075 | 0.8235 | 0.0735 | -0.0028 | 0.0001 | 124 |
| 1985.75 | 0.0117 | 0.8305 | 0.0727 | 0.0071 | -0.0008 | 119 |
| 1986.00 | -0.0003 | 0.8421 | 0.0711 | 0.0116 | -0.0016 | 129 |
| 1986.25 | 0.0027 | 0.8167 | 0.0707 | -0.0255 | -0.0004 | 134 |
| 1986.50 | 0.0003 | 0.8244 | 0.0724 | 0.0078 | 0.0016 | 123 |
| 1986.75 | 0.0030 | 0.8244 | 0.0705 | -0.0001 | -0.0019 | 116 |
| 1987.00 | 0.0004 | 0.8345 | 0.0689 | 0.0102 | -0.0016 | 118 |
| 1987.25 | 0.0005 | 0.8396 | 0.0668 | 0.0051 | -0.0021 | 114 |
| 1987.50 | 0.0026 | 0.8493 | 0.0634 | 0.0097 | -0.0034 | 122 |
| 1987.75 | 0.0027 | 0.8542 | 0.0607 | 0.0049 | -0.0027 | 99 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1988.00 | 0.0105 | 0.8629 | 0.0593 | 0.0087 | -0.0015 | 110 |
| 1988.25 | 0.0006 | 0.8655 | 0.0578 | 0.0026 | -0.0014 | 121 |
| 1988.50 | 0.0085 | 0.8658 | 0.0554 | 0.0003 | -0.0024 | 119 |
| 1988.75 | 0.0005 | 0.8751 | 0.0555 | 0.0093 | 0.0000 | 123 |
| 1989.00 | 0.0070 | 0.8679 | 0.0541 | -0.0071 | -0.0014 | 126 |
| 1989.25 | 0.0024 | 0.8946 | 0.0527 | 0.0266 | -0.0014 | 112 |
| 1989.50 | 0.0047 | 0.8888 | 0.0530 | -0.0058 | 0.0003 | 120 |
| 1989.75 | 0.0050 | 0.8807 | 0.0533 | -0.0081 | 0.0003 | 119 |
| 1990.00 | -0.0003 | 0.8807 | 0.0543 | 0.0000 | 0.0010 | 113 |
| 1990.25 | -0.0004 | 0.8836 | 0.0537 | 0.0030 | -0.0006 | 106 |
| 1990.50 | 0.0049 | 0.8693 | 0.0540 | -0.0143 | 0.0004 | 71 |
| 1990.75 | 0.0026 | 0.8447 | 0.0575 | -0.0246 | 0.0035 | 41 |
| 1991.00 | -0.0056 | 0.8315 | 0.0618 | -0.0132 | 0.0043 | 71 |
| 1991.25 | 0.0002 | 0.8128 | 0.0664 | -0.0187 | 0.0046 | 95 |
| 1991.50 | 0.0082 | 0.8051 | 0.0689 | -0.0077 | 0.0025 | 97 |
| 1991.75 | 0.0054 | 0.7956 | 0.0692 | -0.0095 | 0.0003 | 73 |
| 1992.00 | 0.0042 | 0.7683 | 0.0716 | -0.0273 | 0.0024 | 68 |
| 1992.25 | 0.0094 | 0.7467 | 0.0745 | -0.0216 | 0.0028 | 89 |
| 1992.50 | 0.0072 | 0.7348 | 0.0766 | -0.0119 | 0.0022 | 79 |
| 1992.75 | 0.0068 | 0.7635 | 0.0769 | 0.0287 | 0.0003 | 102 |
| 1993.00 | 0.0093 | 0.7430 | 0.0747 | -0.0205 | -0.0022 | 103 |
| 1993.25 | -0.0020 | 0.7757 | 0.0722 | 0.0327 | -0.0026 | 89 |
| 1993.50 | 0.0004 | 0.7688 | 0.0714 | -0.0070 | -0.0008 | 77 |
| 1993.75 | -0.0007 | 0.7742 | 0.0687 | 0.0055 | -0.0027 | 95 |
| 1994.00 | 0.0089 | 0.7768 | 0.0669 | 0.0026 | -0.0018 | 123 |
| 1994.25 | 0.0028 | 0.7273 | 0.0662 | -0.0495 | -0.0006 | 116 |
| 1994.50 | 0.0087 | 0.7552 | 0.0623 | 0.0280 | -0.0039 | 109 |
| 1994.75 | 0.0006 | 0.7375 | 0.0607 | -0.0178 | -0.0016 | 119 |
| 1995.00 | 0.0016 | 0.7715 | 0.0569 | 0.0341 | -0.0038 | 118 |
| 1995.25 | 0.0002 | 0.7484 | 0.0555 | -0.0232 | -0.0014 | 113 |
| 1995.50 | 0.0052 | 0.7595 | 0.0574 | 0.0112 | 0.0020 | 117 |
| 1995.75 | 0.0061 | 0.7821 | 0.0573 | 0.0226 | -0.0002 | 113 |
| 1996.00 | 0.0048 | 0.7629 | 0.0564 | -0.0192 | -0.0009 | 113 |
| 1996.25 | 0.0040 | 0.7573 | 0.0561 | -0.0056 | -0.0003 | 115 |
| 1996.50 | 0.0114 | 0.7693 | 0.0554 | 0.0120 | -0.0008 | 123 |
| 1996.75 | 0.0018 | 0.7696 | 0.0533 | 0.0003 | -0.0021 | 133 |
| 1997.00 | 0.0056 | 0.7837 | 0.0538 | 0.0141 | 0.0005 | 136 |
| 1997.25 | 0.0025 | 0.7726 | 0.0529 | -0.0111 | -0.0009 | 139 |
| 1997.50 | 0.0084 | 0.7829 | 0.0504 | 0.0103 | -0.0025 | 150 |
| 1997.75 | 0.0079 | 0.7953 | 0.0493 | 0.0124 | -0.0012 | 149 |
| 1998.00 | 0.0035 | 0.8056 | 0.0475 | 0.0103 | -0.0018 | 154 |
| 1998.25 | 0.0077 | 0.8478 | 0.0471 | 0.0422 | -0.0004 | 157 |
| 1998.50 | 0.0060 | 0.8170 | 0.0448 | -0.0308 | -0.0022 | 140 |
| 1998.75 | 0.0106 | 0.8353 | 0.0460 | 0.0183 | 0.0011 | 128 |
| 1999.00 | 0.0108 | 0.8340 | 0.0450 | -0.0013 | -0.0010 | 146 |
| 1999.25 | 0.0031 | 0.8430 | 0.0436 | 0.0090 | -0.0015 | 144 |
| 1999.50 | 0.0062 | 0.8381 | 0.0432 | -0.0049 | -0.0004 | 146 |
| 1999.75 | 0.0098 | 0.8526 | 0.0432 | 0.0145 | 0.0000 | 145 |
| 2000.00 | 0.0119 | 0.8610 | 0.0415 | 0.0084 | -0.0017 | 157 |
| 2000.25 | -0.0144 | 0.8732 | 0.0412 | 0.0122 | -0.0003 | 150 |
| 2000.50 | 0.0163 | 0.8433 | 0.0402 | -0.0298 | -0.0010 | 149 |
| 2000.75 | 0.0030 | 0.8602 | 0.0410 | 0.0168 | 0.0008 | 135 |
| 2001.00 | 0.0010 | 0.8326 | 0.0399 | -0.0276 | -0.0011 | 99 |
| 2001.25 | -0.0056 | 0.8580 | 0.0430 | 0.0254 | 0.0031 | 102 |
| 2001.50 | 0.0099 | 0.8204 | 0.0448 | -0.0376 | 0.0018 | 96 |
| 2001.75 | -0.0005 | 0.7792 | 0.0489 | -0.0412 | 0.0041 | 80 |
| 2002.00 | 0.0064 | 0.7629 | 0.0560 | -0.0163 | 0.0072 | 112 |
| 2002.25 | 0.0100 | 0.7443 | 0.0577 | -0.0186 | 0.0017 | 116 |
| 2002.50 | 0.0036 | 0.7357 | 0.0591 | -0.0086 | 0.0014 | 95 |
| 2002.75 | 0.0016 | 0.7381 | 0.0580 | 0.0024 | -0.0011 | 86 |
| 2003.00 | 0.0018 | 0.7227 | 0.0592 | -0.0153 | 0.0012 | 70 |
| 2003.25 | -0.0006 | 0.7007 | 0.0594 | -0.0220 | 0.0002 | 106 |
| 2003.50 | 0.0077 | 0.6966 | 0.0622 | -0.0041 | 0.0028 | 105 |
| 2003.75 | 0.0174 | 0.7030 | 0.0617 | 0.0064 | -0.0005 | 119 |
| 2004.00 | 0.0063 | 0.7107 | 0.0588 | 0.0077 | -0.0029 | 126 |
| 2004.25 | 0.0042 | 0.7099 | 0.0575 | -0.0007 | -0.0014 | 113 |
| 2004.50 | 0.0043 | 0.7277 | 0.0566 | 0.0177 | -0.0009 | 118 |
| 2004.75 | 0.0045 | 0.7372 | 0.0550 | 0.0095 | -0.0016 | 117 |
| 2005.00 | 0.0051 | 0.7445 | 0.0546 | 0.0073 | -0.0004 | 111 |
| 2005.25 | 0.0078 | 0.7371 | 0.0535 | -0.0074 | -0.0011 | 100 |
| 2005.50 | -0.0026 | 0.7611 | 0.0517 | 0.0240 | -0.0018 | 92 |
| 2005.75 | 0.0030 | 0.7585 | 0.0503 | -0.0026 | -0.0014 | 85 |
| 2006.00 | 0.0035 | 0.7761 | 0.0502 | 0.0176 | -0.0001 | 98 |
| 2006.25 | 0.0060 | 0.7697 | 0.0479 | -0.0064 | -0.0023 | 85 |
| 2006.50 | -0.0013 | 0.7782 | 0.0472 | 0.0085 | -0.0007 | 87 |
| 2006.75 | -0.0024 | 0.7976 | 0.0471 | 0.0194 | -0.0001 | 110 |
| 2007.00 | 0.0005 | 0.7573 | 0.0452 | -0.0402 | -0.0019 | 107 |
| 2007.25 | -0.0030 | 0.7670 | 0.0459 | 0.0097 | 0.0007 | 92 |
| 2007.50 | 0.0096 | 0.7484 | 0.0456 | -0.0186 | -0.0003 | 92 |

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|---|---|---|---|---|---|---|
| 2007.75 | 0.0061 | 0.7560 | 0.0472 | 0.0076 | 0.0016 | 73 |
| 2008.00 | 0.0013 | 0.7321 | 0.0487 | -0.0239 | 0.0014 | 56 |
| 2008.25 | -0.0064 | 0.7457 | 0.0505 | 0.0136 | 0.0018 | 38 |
| 2008.50 | 0.0069 | 0.6924 | 0.0539 | -0.0532 | 0.0034 | 53 |
| 2008.75 | -0.0003 | 0.6679 | 0.0608 | -0.0246 | 0.0069 | 43 |
| 2009.00 | -0.0132 | 0.6100 | 0.0694 | -0.0578 | 0.0086 | 41 |
| 2009.25 | 0.0042 | 0.5482 | 0.0836 | -0.0619 | 0.0142 | 66 |
| 2009.50 | 0.0071 | 0.5158 | 0.0935 | -0.0324 | 0.0099 | 75 |
| 2009.75 | 0.0097 | 0.4823 | 0.0967 | -0.0335 | 0.0032 | 76 |
| 2010.00 | 0.0171 | 0.5012 | 0.0998 | 0.0189 | 0.0031 | 81 |
| 2010.25 | 0.0027 | 0.4644 | 0.0990 | -0.0368 | -0.0007 | 81 |
| 2010.50 | 0.0050 | 0.5160 | 0.0972 | 0.0516 | -0.0018 | 65 |
| 2010.75 | 0.0059 | 0.4830 | 0.0954 | -0.0330 | -0.0018 | 72 |
| 2011.00 | 0.0076 | 0.5106 | 0.0959 | 0.0276 | 0.0005 | 77 |
| 2011.25 | -0.0058 | 0.4882 | 0.0911 | -0.0224 | -0.0048 | 77 |
| 2011.50 | 0.0065 | 0.5134 | 0.0914 | 0.0252 | 0.0003 | 44 |
| 2011.75 | -0.0004 | 0.5071 | 0.0907 | -0.0063 | -0.0007 | 55 |
| 2012.00 | 0.0054 | 0.5341 | 0.0872 | 0.0269 | -0.0035 | 81 |
| 2012.25 | -0.0014 | 0.5313 | 0.0833 | -0.0028 | -0.0039 | 86 |
| 2012.50 | 0.0023 | 0.5276 | 0.0825 | -0.0037 | -0.0008 | 78 |
| 2012.75 | -0.0015 | 0.5617 | 0.0808 | 0.0341 | -0.0017 | 89 |
| 2013.00 | -0.0055 | 0.5372 | 0.0788 | -0.0245 | -0.0020 | 85 |
| 2013.25 | 0.0073 | 0.5684 | 0.0781 | 0.0311 | -0.0006 | 97 |
| 2013.50 | -0.0017 | 0.5749 | 0.0760 | 0.0065 | -0.0021 | 95 |
| 2013.75 | 0.0042 | 0.5819 | 0.0732 | 0.0070 | -0.0028 | 80 |
| 2014.00 | 0.0102 | 0.6021 | 0.0702 | 0.0202 | -0.0031 | 91 |
| 2014.25 | -0.0096 | 0.6013 | 0.0671 | -0.0008 | -0.0030 | 99 |
| 2014.50 | 0.0071 | 0.6265 | 0.0627 | 0.0253 | -0.0045 | 92 |
| 2014.75 | 0.0084 | 0.6566 | 0.0615 | 0.0301 | -0.0012 | 108 |
| 2015.00 | -0.0012 | 0.6360 | 0.0577 | -0.0206 | -0.0038 | 122 |
| 2015.25 | 0.0035 | 0.6870 | 0.0563 | 0.0510 | -0.0014 | 121 |
| 2015.50 | 0.0029 | 0.6805 | 0.0547 | -0.0065 | -0.0016 | 109 |
| 2015.75 | 0.0025 | 0.6715 | 0.0518 | -0.0090 | -0.0028 | 103 |
| 2016.00 | -0.0035 | 0.6765 | 0.0509 | 0.0050 | -0.0009 | 101 |
| 2016.25 | -0.0073 | 0.6820 | 0.0503 | 0.0055 | -0.0006 | 102 |
| 2016.50 | 0.0047 | 0.6864 | 0.0494 | 0.0043 | -0.0009 | 98 |
| 2016.75 | 0.0029 | 0.6923 | 0.0497 | 0.0060 | 0.0003 | 106 |
| 2017.00 | 0.0015 | 0.7114 | 0.0480 | 0.0191 | -0.0017 | 117 |
| 2017.25 | 0.0001 | 0.7464 | 0.0471 | 0.0350 | -0.0009 | 114 |
| 2017.50 | 0.0039 | 0.7051 | 0.0440 | -0.0413 | -0.0031 | 113 |
| 2017.75 | 0.0034 | 0.7301 | 0.0439 | 0.0251 | -0.0001 | 121 |