The Cyclical Behavior of Unemployment and Wages under Information Frictions*

Camilo Morales-Jiménez†

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Abstract

I propose a new mechanism for sluggish wages based on workers' noisy information about the state of the economy. Wages do not respond immediately to a positive aggregate shock because workers do not (yet) have enough information to demand higher wages. Firms, who have perfect information, do not reveal their information and instead extract an informational rent. This increases firms' incentives to post more vacancies, which makes unemployment volatile and sensitive to aggregate shocks. The model is robust to two major criticisms of existing theories of sluggish wages and volatile unemployment: flexibility of wages for new hires and procyclicality of the opportunity cost of employment. Calibrated to U.S. data, the model explains 60% of overall unemployment volatility. In line with empirical evidence, the response of unemployment to TFP shocks is large, hump-shaped, and peaks one year after the TFP shock, while the response of the aggregate wage is weak and delayed, peaking after two years. In line with empirical evidence, this model predicts a reallocation of employment from low to high-paying firms during expansions. I show that this reallocation is intensified by sluggish wages, and has significant effects on newly-hired workers as they find more and better paying jobs in booms.

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†Contact: morales-jimenez@econ.umd.edu

1 Introduction

Search and matching models are an appealing way to study fluctuations in the labor market, as they define unemployment in a manner that is consistent with statistical agencies' convention and describe in an attractive way the functioning of the labor market, how firms and workers are matched and how wages are negotiated.[1] However, Shimer (2005) pointed out the low volatility of unemployment predicted by the standard search and matching model, hence giving rise to a large body of literature studying the amplifying effects of sluggish wages. This approach to the Shimer Puzzle has been criticized in recent years on the basis that, empirically, wages for new hires exhibit little rigidity while the opportunity cost of employment is pro-cyclical.[2] In this paper, I propose a new mechanism for sluggish wages based on workers' noisy information about the state of the economy that is robust to the aforementioned critiques and that generates business cycle dynamics for unemployment and wages that are consistent with the empirical evidence.[3]

In my model, wages for new hires are flexible, but wages do not adjust immediately to the true state of the economy because agents learn slowly about aggregate shocks. This delayed adjustment in wages increases firms' incentives to expand employment, making unemployment volatile and sensitive to aggregate shocks. My model is able to explain 60% of overall unemployment volatility and generates wage semi-elasticities with respect to unemployment of around -3%, which is a conservative number in the literature.

The model presented in this paper is in many respects similar to a standard RBC model with search and matching in the labor market. I introduce heterogeneous firms and assume that they differ in their permanent total factor productivity levels, which are public information. Hence, in equilibrium, the most productive firms are larger and pay higher wages. In order to distinguish between new hires coming from unemployment and job changers, I assume that workers search on the job for better-paid jobs. However, the most important distinction in this model versus the existing literature is that workers (households) face information frictions regarding aggregate

[1] Rogerson and Shimer (2011) assess in more detail how models with search frictions have shaped our understanding of aggregate labor market outcomes.

[2] For example, Rudanko (2009) shows in a model with long-term contracts that wage rigidity does not increase unemployment volatility as long as wages for new hires are flexible. Mortensen and Nagypal (2007) argue that the literature has overemphasized the need for sticky wages to increase unemployment volatility in the standard model of Mortensen and Pissarides (1994) and highlight three other features that could help explain the Shimer puzzle: (1) low elasticity of the matching function with respect to vacancies, (2) low value for the flow opportunity cost of employment, and (3) strong feedback from the job-finding rate to wages. Similarly, Pissarides (2009) critiques the assumption of sticky wages based on empirical evidence that wages for new hires (job changers or new hires coming from unemployment) are more pro-cyclical than are wages for existing workers (e.g. Beaudry & DiNardo, 1991; Bils 1985; Haefke, Sonntag & van Rens 2013; Shin, 1994).

[3] Even though this paper focuses on labor market fluctuations, whether or not sticky wages are a source of fluctuations over the business cycle is not only of interest for labor economics. For example, Christiano, Eichenbaum, Evans (2005) and Smets and Wouters (2007) find that nominal wage stickiness is one of the most important frictions for understanding macroeconomic dynamics under nominal shocks.

conditions. In particular, the only source of aggregate uncertainty is aggregate total factor productivity (TFP), which is not directly observed by workers. Instead, workers form expectations based on a public and noisy signal that they receive each period. This implies that TFP shocks are only partially perceived by workers, who slowly learn about aggregate conditions as time goes by. This information friction affects households' and workers' decisions including consumption and saving. Firms and workers negotiate wages each period. Workers negotiate wages based on their beliefs about the aggregate state of the economy. Hence, after a positive productivity shock, wages remain relatively constant because workers do not immediately possess the proper information to demand higher wages, which generates sluggish wages within jobs. In other words, if productivity increases at time t, the wage demanded by workers at firm j at time t will not be very different from the wage that workers demanded at firm j at time $t-1$.

The persistence in wages within jobs increases firms' incentives to hire workers in an expansion as they get to keep a larger fraction of the match surplus. However, in equilibrium, the high-paying/most-productive firms hire proportionally more new workers than the low-paying/less-productive firms in response to a positive productivity shock. This is because there is a significant increase in job-to-job flows as a consequence of the increase in employment, which reduces the average duration of a match for less productive firms and therefore the value of an additional worker. Given that firms have to pay a cost for recruiting new workers, low-wage less-productive firms end up paying this cost more frequently than more productive firms.[4] In addition, an increase in aggregate TFP reduces the pool of unemployment, which makes it more difficult for low-paying firms to find new workers but doesn't significantly affect high-wage firms, as they rely more on the pool of employed searchers to fill a vacancy.

In addition to this differential employment growth rate, I also find in my model that high-paying firms tend to exhibit more *"flexible"* wages in the sense that their wages increase more during expansions. This is a direct consequence of the differential employment growth rate. Notice that an increase in consumption and employment at firm j increases the opportunity cost of employment at that firm because workers would prefer to enjoy more free time.[5] In an expansion, high-paying firms have to offer higher wages in order to compensate their workers not only for the increase in consumption but also for the larger increase of employment.[6] However, in an expansion, low-paying firms do not have to increase their wages as much as high-paying firms because, even though

[4]For example, Davis, Faberman, and Haltiwanger (2013) find a large heterogeneity in hires, separations and vacancy duration across firms. In addition, they find that firms with higher employment growth have higher vacancy yields.

[5]Following Chodorow-Reich and Karabarbounis (2014), the *flow opportunity cost of employment* in my model is the sum of two components: (1) foregone unemployment benefits and (2) the foregone value of non-working activities in terms of consumption. Hence, the faster firm j grows, the larger the opportunity cost of employment for its employees, as the foregone value of non-working activities in terms of consumption increases.

[6]Notice that an increase in consumption makes the value of non-working activities rise in terms of consumption.

consumption increases, employment at low-paying firms is expanding at a lower rate. Hence, even though wages within jobs adjust slowly to the true state of the economy, the average wage for new hires exhibits a large response to productivity shocks on impact. This is because a new hire faces more and better-paying job opportunities in an expansion than in a recession. However, even after controlling for this composition effect, my model model generates wage semi-elasticities with respect to the unemployment rate for new hires and job changers of around -3%, which is similar to the estimate of Pissarides (2009) and larger than the estimates of Hagedorn and Manovskii (2013) and Gertler et al. (2014).

What does the empirical evidence tell us about the mechanism proposed in this paper? Using employer-employee data for the U.S., Kahn and McEntarfer (2014) find that employment at high-wage firms is more sensitive to the business cycle. According to their estimates, the differential employment growth rate (high minus low-paying firms) is negatively correlated with the unemployment rate, and this difference is not driven by a more cyclically-sensitive product demand for high-paying firms or because high-wage firms suffer more from earnings rigidities. Hence, a decline in unemployment is associated with a larger increase in employment at high-wage firms. In addition, they find that during a downturn, the distribution of new matches shifts towards low-paying firms, whose separation rate declines more than high-paying firms because of the reduction in job-to-job transitions. Therefore, even though employment changes are more cyclical at high-paying firms, gross worker flows are more cyclical at low-paying firms. Using employer-employee data for the U.S., Haltiwanger, Hyatt and McEntarfer (2015) find that job-to-job flows do reallocate workers from lower-paying to higher-paying firms and that this reallocation is highly procyclical. They find that net employment growth for high-wage firms is substantially greater in times of low unemployment compared with low-wage firms, which is driven by net poaching from low-wage to high wage firms. Similarly, Moscarini and Postel-Vinay (2012) find that employment growth is more negatively correlated with the unemployment rate at large high-paying firms than at small low-paying firms. Moreover, they find that this fact holds mainly *within*, not across, sectors and states. In an earlier paper, Moscarini and Postel-Vinay (2008) using different data sources conclude that *"following a positive aggregate shock to labor demand, wages respond little on impact and start rising when firms run out of cheap unemployed hires and start competing to poach and to retain employed workers"* (p, 2). Hence, wages increase for two reasons: first, workers are paid progressively more, and second workers move to higher-paying firms.[7]

Meanwhile, my assumption about information frictions finds empirical support in the work by

[7]Similarly, there is a large literature that points out the existence of sectoral wage differences for the U.S. and differences in the cyclical behavior of employment across sectors. Some examples are: Abraham and Katz (1986), Davis and Haltiwanger (1991), Haisken-DeNew and Schmidt (1995), Horrace and Oaxaga (2001), Juhn, Muphy, and Pierce (1993), Krueger and Summer (1988), Rielly and Zanchi (2003). One interpretation of these facts is that the sectors more subject to cyclical demand pay higher wages in order to compensate workers for higher unemployment risk (e.g. Barlevy, 2001, Okun, 1973, McLaughlin & Bils, 2001).

Coibion and Gorodnichenko (2012). They compute forecast errors made by professional forecasters, consumers and firms, and document that forecast errors are not consistent with the predictions of a model with perfect information. Rather, they find that forecast errors follow a mean reverting process with a persistence between 0.8 and 0.9. According to their results, the behavior of forecast errors is more consistent with a model in which agents receive noisy signals about aggregate conditions, as I assume in this paper. In addition, Carroll (2003) formulates and finds evidence in favor of a model in which consumers have a larger degree of information rigidity than other agents. Similarly, Roberts (1998) finds evidence of non-rational expectations in survey data, and Branch (2004) argues that surveys reject the rational expectation hypothesis not because agents use an *ad hoc* expectation rule, but rather because agents optimally decide not to use a more complicated expectation (predictor) function.

I calibrate my model using U.S. data for the period 1964-2014. In order to address the cyclicality of wages for job stayers versus new hires, I use the Current Population Survey (CPS) microdata in order to compute the average wage for these two groups of workers controlling for composition effects (e.g. Solon, Barsky & Parker, 1994; Haefke, Sonntag & van Rens, 2013; Muller, 2012). Given that the driving force of this model is shocks to aggregate productivity, I follow the literature that investigates the effects of TFP innovations in order to estimate the fraction of business cycle moments that can be explained by aggregate *temporary* productivity shocks (e.g. Barnichon, 2010; Basu, Fernald & Kimball, 2006; Blanchard & Quah, 1989; Christiano, Eichenbaum & Vigfusson, 2003, 2005; Gali, 1999). I find that between 70 and 75% of overall business cycle volatility in labor market quantities such as unemployment, vacancies and the vacancy-unemployment ratio can be explained by *temporary* TFP innovations. In contrast, only 25% of the overall volatility in wages can be attributed to such transitory productivity shocks. For quantity variables, I find significant Impulse Response Functions (IRFs) to productivity shocks that exhibit a hump-shaped behavior, peaking one year after the TFP shock. The maximum responses indicate that, following a 1% increase in productivity, the total number of unemployed workers declines by 6%, vacancies increase by 7% and the vacancy-unemployment ratio goes up by 15%. I find that wages, adjusted for composition effects, are procyclical, but I do not find significant differences in the cyclicality of wages for different groups of workers. In contrast to labor market quantities, IRFs for wages are weak and delayed, peaking 2 years after the TFP shock. After a 1% increase in aggregate productivity, wage responses are very small in absolute value during the first 3 quarters (less than 0.2%). Even though wages increase 1% above their trend 2 years after the shock, this is not statistically significant, indicating that wage responses to *transitory* TFP shocks are weak.

The model calibrated to the U.S. economy is able to explain between 60 and 70% of the volatility of unemployment, vacancies, and the vacancy-unemployment ratio and 90% of the volatility in output, consumption and investment that is due to TFP shocks. A graphical inspection reveals that the dynamics predicted by my model are very close to the dynamics estimated in the data. My model generates IRFs that are hump-shaped with peaks consistent with the empirical evidence that I present.

I also show that assuming sticky wages for continuing workers amplifies the unemployment response to productivity shocks, in contrast to previous literature for which the wage of job stayers is irrelevant for vacancy decisions. If a worker has to negotiate her wage for the following n periods, she gives up using the new information she would otherwise be using in the future. Therefore, wages take longer to adjust to the true state of the economy, which increases the firm's incentives to post vacancies. Similarly, I show that assuming that firms face the same information frictions would reinforce my results. If firms observe their overall productivity at all times but cannot distinguish between idiosyncratic productivity shocks and aggregate shocks, they will partially attribute aggregate shocks to idiosyncratic conditions. Hence, firms will underestimate the decline in the separation rate that is due to productivity shocks and will tend to post even more vacancies. Finally, my results are robust to assuming that workers searching on-the-job take a lower-paying job with an exogenous probability.

This work builds on the literature that addresses the Shimer puzzle (Shimer, 2005; Constain & Reiter, 2008) by studying the amplifying effects of sluggish wages on job creation.[8] This literature is large; some examples are: Blanchard and Gali (2010), Christiano, Eichenbaum and Trabandt (2014), Elsby (2009), Gertler and Trigari (2009), Hall (2005), Kennan (2009), Menzio (2005), and Venkateswaran (2013). My paper differs in at least three aspects with respect to this literature. First, I propose a new mechanism for sticky wages based on workers that face information frictions regarding aggregate variables. This mechanism, in contrast to the previous literature, does not rely on any assumption about the persistence of aggregate shocks (Menzio, 2005) or the distribution of firms (Kennan, 2009).[9] In contrast to Venkateswaran (2013), I show that assuming firms face information frictions does not generate sticky wages but can amplify the unemployment response to productivity shocks.[10] As in Menzio (2005) and Kennan (2009), what drives sticky wages in my model is the fact that workers are willing to work for wages that do not adjust to the true state of

[8]There are alternative sources of fluctuations that increase unemployment volatility that are not studied in this paper. For example, den Haan, Ramy, and Watson (2000) show that endogenous job destruction increases the response of unemployment to productivity shocks, and Carlsson and Westermark (2015) point out that sticky wages for job stayers may increase the strength of this channel. Similarly, recent literature has pointed out that sticky wages for job stayers may increase the unemployment volatility if firms face financial frictions (Schoefer, 2015) or if labor effort is variable (Bils, Chang & Kim, 2014), even though sticky wages for continuing workers do not directly affect vacancy decisions in their models.

[9]Menzio (2005) and Kennan (2009) derive endogenous sticky wages based on firms that have private information about their labor productivity. In Menzio (2005), aggregate shocks cannot be very persistent. Otherwise, workers would demand higher wages. In Kennan's model, the standard deviation of idiosyncratic productivity cannot be large.

[10]Venkateswaran (2013) assumes firms that face information frictions regarding aggregate variables. In his model, after a positive productivity shock, firms do not offer higher wages because they partially attribute aggregate shocks to idiosyncratic conditions, which makes firms post more vacancies.

the economy. That is, it is not enough to explain why firms offer wages that are very persistent; workers need to be willing to accept them.

A second difference of my paper with respect to the previous literature is that my model is able to generate significant unemployment volatility in spite of the procyclicality of the *flow opportunity cost of employment* (FOCE), which is the sum of the foregone unemployment benefits and the the foregone value of non-working activities valued in terms of consumption. According to Chodorow-Reich and Karabarbounis (2014), the FOCE is very procyclical, which weakens or breaks down the results of influential papers such as Hall and Milgrom (2008) and Hagedorn and Manovskii (2008).[11] This point is also related to the argument of Brugemann and Moscarini (2010) that assuming rent rigidities (wages in excess of the value of unemployment) can account for at most 20% of the volatility in the job-finding rate. In this paper, even though the FOCE is procyclical, I still find significant responses of labor market quantities to shocks. This is due to the timing of the model and the *real* part of the information friction. Given that households make consumption and saving decisions based on the same information friction, investment (capital accumulation) absorbs most of the shock in the initial periods, which prevents consumption and the FOCE from increasing. Hence, even though the FOCE eventually rises, it takes time because workers (not firms) have information frictions regarding aggregate variables. To test this assumption, I show that my model predicts dynamics for investment that are consistent with the data and does a good job matching business cycle moments for consumption.

Finally, in contrast to previous literature, this paper looks at the distributional implications of productivity shocks. I show how and why high-wage firms expand employment the most during an expansion and how this mechanism generates different wage dynamics across firms. In this paper, even though the information friction is the same for all agents, wages at low-paying firms are less sensitive to the business cycle than wages at high-paying firms. This is a result that other models with sticky wages are unable to reproduce. In fact, in a standard *New-Keynesian* model, a higher cyclicality of wages at high-wage firms would indicate a lower degree of overall wage rigidity.

This paper is also related to the literature about information frictions. This paper is close in spirit to Lucas (1972), where agents' inability to distinguish between aggregate and idiosyncratic shocks generates money non-neutrality. Following Angeletos and La'O (2012) the information friction presented in this paper has both a nominal and a real part. That is, noisy information about aggregate conditions affects not only price (wage) decisions, but also real allocations (saving, consumption, search intensity). As explained above, the real part of the information friction plays an important role in explaining the dynamics of the model. Even though this information structure seems exogenous, paying limited attention to aggregate shocks is a standard result in the rational

[11] Chodorow-Reich and Karabarbounis (2014) critique extends to all papers that assume a fixed and therefore acyclical FOCE, including Menzio (2005) and Kennan (2009).

inattention literature that started with Sims (2003). For example, Mackowiak and Wiederhold (2009) present a model in which agents optimally decide to receive a noisy signal about aggregate conditions, as I assume in this paper, because acquiring information is costly. Similarly, Acharya (2014) and Reis (2006a, 2006b) show that agents optimally decide to update their information set sporadically when they face a cost of acquiring and processing information.

Finally, this paper is related to the literature that studies the cyclicality of wages over the business cycle. On the one hand, many studies conclude that the degree of wage cyclicality is small, based in part on empirical evidence suggesting that nominal wages adjust, on average, every 4 quarters in the U.S. (e.g. Kahn, 1997; Barattieri, Basu & Gottschalk, 2014).[12,13] However, Pissarides (2009) argues that vacancy decisions depend only on the wage for new hires and points out that the wage elasticity with respect to unemployment for new hires is around -3%, in comparison with an elasticity of -1% for job stayers. The Pissarides critique has been recently challenged by Gertler, Huckfeldt and Trigari (2014), who argue that the evidence presented by Pissarides is based only on job changers. Using PSID data, Gertler et al (2014) do not find that wages for new workers are more procyclical than wages for job stayers and find that the wage elasticity for job changers with respect to unemployment is -1.7%, which they argue is driven by changes in match quality.[14] Whether or not wages for new hires are more procyclical than wages for existing workers is still an open question and is beyond the scope of this paper.[15] Nevertheless, I use CPS microdata in order to construct the average wage for job stayers and new hires (adjusted for composition effects) and assess the predictions of my model. It is worth noting that in my model wages for new hires are flexible and I show that my model is able to reproduce a wage elasticity with respect to unemployment for new hires and job changers of around -3%, which is not a target in my calibration.[16] Hence, this paper points out that wage flexibility for new hires does not imply that wages adjust immediately to the true state of the economy.

The rest of this paper is organized as follows: I present my model in Section 2 and explain the numerical computation of it in Section 3. Section 4 presents quantitative analysis. First, I look at

[12]For example, Christiano et al (2013) argue that a *"successful model must have the property that wages are relatively insensitive to the aggregate state of the economy"* (p, 3). Similary, Abraham and Haltiwanger (1995) find that the relation between aggregate wages and output does not always seem to be contemporaneous. They conclude that it is not possible to say whether real aggregate wages are procyclical or not and that in general the cyclicality is small.

[13]In contrast to other countries, there is no seasonal pattern in wage adjustments in the U.S. Le Bihan, Montornes and Heckel (2012), Lunnemann and Wintr (2009), and Sigurdsson and Sigurdardottir (2011) present evidence of nominal wage adjustment for France, Luxembourg and Iceland that exhibits seasonal patterns.

[14]They do not find that wages for job changers are more procyclical than wages for job stayers when they include match fixed effects.

[15]For example, Hines, Hoynes, and Krueger (2001) argue that much of the cyclicality of wages estimated by Solon, et al (1994) comes from weighting the data by hours worked.

[16]Based on their empirical results, Gertler et al (2014) build a model in which the wage elasticity of job changers is driven by changes in match quality. Menzio and Shi (2011) also present a model in which job to job transitions are driven by random match quality.

the data for the U.S., estimate the fraction of the business cycle moments that can be explained by TFP shocks, and compute the business cycle dynamics of some relevant variables after an aggregate productivity shock. Then, I calibrate my model and compare the model's predictions with my empirical analysis. In Section 5, I discuss some alternative issues and extensions, and Section 6 concludes.

2 Theoretical Framework

The model presented in this section is, in many aspects, similar to a standard real business cycle model with search and matching in the labor market as in Andolfatto (1996) and Merz (1995). I introduce job changers in this model following the theoretical framework of Moscarini and Postel-Vinay (2013) and Burdett and Mortensen (1998). The main difference of my model with respect to the relevant literature is that workers face information frictions about aggregate conditions. As in Lucas (1972), workers form expectations about current aggregate economic conditions based on noisy signals.

2.1 Model Overview

There are two types of agents in this economy, households and firms. There is a representative household in the economy made up of a continuum of workers that supplies capital and labor to firms and owns all firms in the economy. The household derives utility from consumption and leisure and discounts future utility at rate β. Capital is supplied in a perfectly competitive market at the capital rental rate r_t and depreciates at rate δ_k, while labor supply is subject to search frictions. I assume complete consumption insurance, which implies that workers seek to maximize income for the household. A worker can be employed or unemployed at each point in time. Unemployed workers receive unemployment compensation b and are matched with a firm with probability q. Employed workers are separated from their job with exogenous probability δ_h, in which case they must spend at least one period in unemployment before they can be matched with another firm. Employed workers can search on the job. An employed worker at firm j searches with intensity i_j and is matched with another firm with probability $q \cdot i_j$. However, employed workers only change jobs if they find a firm that offers an equal or better wage. Search is costly for employed workers as they have to pay a cost equal to $\mu\frac{(i_j-\bar{i})^{1+\epsilon}}{1+\epsilon}$; $\epsilon > 1$ and $i_j \geq \bar{i}\ \forall j$.

There is a continuum of firms indexed by j with mass normalized to 1. All firms produce a homogeneous good that is sold in a competitive market to the household and can be used for consumption or capital accumulation. *A priori* the only difference among firms is their (permanent) total factor productivity (TFP) level, which is denoted by a_j. Without loss of generality, I assume that a_j is increasing in j. Hence, $a_x \geq a_y$ for all $x \geq y$. As in Moscarini and Postel-Vinay (2013), the most productive firms pay higher wages and are larger in equilibrium.[17] Firms produce with capital k_j and labor h_j, through a concave production function. Firms' output is denoted by $y_j = e^{a_j+a}\left(k_j^{\alpha}h_j^{1-\alpha}\right)^{\gamma}$; where $\gamma < 1$ and a stands for aggregate TFP, which is common to all firms. At the beginning of each period, firms rent capital and open new vacancies, v_j. A vacancy is matched with a worker with probability $\tilde{q}$. If a vacancy is matched with an unemployed worker, the vacancy is filled with probability 1. However, if a vacancy is matched with an employed worker, the vacancy is filled only if the worker is coming from a less productive firm. As is standard, new workers (filled vacancies) become productive in the subsequent period. In order to avoid biasing my results in favor of high-wage firms, I assume a hiring cost of the form $\frac{\kappa}{1+\chi}(\tilde{q}_j v_j)^{1+\chi}$, where $\chi > 0$ and $\tilde{q}_j$ is the job filling rate for firm j.[18]

The total number of matches in the economy $m(v, s)$ is an increasing function in the total number of vacancies ($v = \int_0^1 v_j dj$) and the total number of job searchers ($s = u + \int_0^1 (1-\delta_h) i_j h_j dj$, where $u = 1 - \int_0^1 h_j dj$ is the number of unemployed workers). Following the literature, $m(v, s)$ is assumed to be homogeneous of degree 1. Hence, $q = m(\theta, 1)$ and $\tilde{q} = m(1, \theta^{-1})$ where $\theta = v/s$ is labor market tightness.

Firms and workers negotiate wages, w_j, each period in order to split the expected match surplus according to a simple game: firms make a wage offer that can be accepted or rejected, in the latter case workers make a *take-it-or-leave-it offer* to firms with exogenous probability ϑ. Hence, in steady state, ϑ is the fraction of the match surplus that goes to workers.

The only source of aggregate uncertainty is aggregate total factor productivity a, which follows an AR(1) process. However, a is not directly observed by workers in this economy. Instead, every period there is a public and noisy signal $\hat{a}$ about the current level of aggregate TFP. This signal is observed by workers and firms, and this is common knowledge. Based on the expectations

[17]While there is evidence in favor of a positive relationship between firm size and wages (e.g. Brown & Medoff, 1989; Moscarini & Postel-Vinay, 2008), there is also evidence indicating that firm age is as well important for understanding differences in cyclical behavior across firms (e.g. Haltiwanger, Jarmin & Miranda 2013; Fort, Haltiwanger, Jarmin, & Miranda 2013). In particular, Haltiwanger et al. (2015) point out the importance of classifying firms by wage instead of size. This paper abstracts from firm entry and exit. Hence, even though in my paper larger firms are more productive and pay higher wages, it is possible to think about the firm's size in the long run. However, I expect my results to be robust to firm entry and exit since firm size does not affect my mechanism.

[18]Assuming a vacancy posting cost instead would disproportionally affect low-wage firms, as they have to post even more vacancies in expansions as a consequence of a larger decline in their job filling rate. However, in the context of this model, assuming a hiring cost function does not imply that vacancy decisions do not depend on labor market conditions. On the contrary, job-to-job transitions induce changes in the separation rate within firms that significantly influence the value of a new vacancy. Pissarides (2009) argues that hiring costs are a plausible assumption and discusses how assuming a hiring rather than vacancy costs may change the results in the standard model. However, I show that my calibrated model with perfect information does not do a good job matching the unemployment and wage dynamics observed in the data. On the other hand, Gertler and Trigari (2009) and Gertler et al. (2014) assume a quadratic cost of adjusting employment in order to ensure a determinate equilibrium. I prefer a hiring cost over a cost of adjusting employment as a hiring cost does not bias my results in favor of high-wage firms. However, my results are not sensitive to assuming a cost of adjusting employment.

derived from this signal, workers make wage demands (in a sense that will be explained below) and choose their search intensity, and the household makes consumption/savings decisions. Even though workers do not perfectly observe aggregate TFP, the idiosyncratic TFP level a_j for each firm is public information. In the benchmark model, firms have perfect information about aggregate productivity.[19]

The timing of the model each period is as follows:

1. Aggregate TFP is realized.
2. The public signal is received and workers form expectations.
3. Wages are negotiated.
4. Firms rent capital and post vacancies.
5. Production takes place, and factors are paid.
6. The household makes a consumption decision based on the beliefs derived from the signal $\hat{a}$.
7. A fraction $(1-\delta_h)$ of employed workers is not separated and choose their search intensity i_j based on the beliefs derived from the signal $\hat{a}$.
8. A fraction $(1-\delta_h)i_j q$ of employed workers at firm j is matched with another firm, and a fraction q of unemployed workers finds a new job.
9. A fraction $(1-\delta_h)i_j q F_j$ of employed workers leaves firm j to join another firm, where F_j is the probability for firm j's employees of being matched with a firm with higher a_j.

2.2 Household

There is a representative household made up of a continuum of members with mass normalized to 1.[20] The household is the owner of all firms in the economy, and it supplies capital and labor to firms. Capital is supplied in a perfectly competitive market at the rental rate r, while labor supply is subject to search frictions. I assume complete consumption insurance, which implies that workers seek to maximize income for the household. Consumption and savings decisions are made at the household level, but household members make their decisions based on the same information set $\mathcal{I}_h$. Throughout this paper, $E_{\mathcal{I}_h}[x]$ is the expected value of x conditional on the information set $\mathcal{I}_h$, and $E[x]$ is the expectation conditional on perfect information.

[19] In section 5.2, I show that my results are reinforced when firms face information frictions.

[20] For expositional purposes, I derive in this section the value of employment and unemployment based on the model assumptions. For a detailed derivation of these value functions as in Merz (1995) and Andolfatto (1996), see appendix C.

2.2.1 Consumption and Saving

Consumption and savings decision are made at the household level in order to maximize the utility function

$$\mathbb{U}(\omega, \Omega) = \frac{c^{1-\sigma}}{1-\sigma} - \Psi \int_0^1 \frac{h_j^{1+\xi}}{1+\xi} dj + \beta E\left[\mathbb{U}(\omega', \Omega')\right] \tag{1}$$

subject to the budget constraint (2) and a perceived law of motion for the economy (3):

$$\begin{aligned} c + k' \leq &(r + 1 - \delta_k)k + \int_0^1 w_j h_j dj + \int_0^1 \pi_j dj + b \cdot u - T \\ &- \int \mu \frac{(i_j - \bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h) h_j dj \end{aligned} \tag{2}$$

$$\Omega' = \lambda^h(\Omega) \tag{3}$$

where $'$ denotes next period's value. $\omega = \{k, \{h_j\}_{j=0}^1, \mathcal{I}_h\}$ is the vector of state variables for the representative household, and Ω is a vector that summarizes the aggregate state of the economy. c is consumption, k is capital, w_j is the wage paid by firm j, and π_j stands for firm j's profits. $u = \int_0^1 (1-h_j) dj$ is the total number of unemployed workers, and b is unemployment compensation, which is financed by *lump sum* taxes ($T = b \cdot u$). The last term in (2) is the total cost of on-the-job search, which will be discussed later in detail. The household and its members form expectations based on their information set $\mathcal{I}_h$ and on a perceived law of motion for the economy ($\lambda^h(\cdot)$). Therefore, the problem for the household is given by:

$$\begin{aligned} \max_{c,k'} \quad & E_{\mathcal{I}_h}\{\mathbb{U}(\omega, \Omega)\} \\ & \text{s.t.} \\ (2), \quad & (3) \end{aligned}$$

This lead to the first order condition for consumption:

$$c^{-\sigma} = \beta E_{\mathcal{I}_h}\left[(1 - \delta + r')c'^{-\sigma}\right] \tag{4}$$

It is worth noting that the consumption decision is also affected by information frictions because the expectation in equation (4) is conditional on the information set $\mathcal{I}_h$. In other words, information frictions affect not only the wage bargaining process as described in section 2.5, but also real allocations.[21] To the extent that aggregate shocks are partially perceived, the household will

[21] Following the terminology of Angeletos and La'O (2012), the information friction is real since it affects both prices and real allocations.

respond to productivity innovations by accumulating capital in an attempt to smooth consumption through time. As a result, the marginal disutility of labor (in terms of consumption) does not increase, which prevents wages from going up. This mechanism will be clear in section 2.5.

2.2.2 Workers

A worker can be employed or unemployed at each point in time. Unemployed workers receive unemployment compensation b and are matched with a firm with probability q. Conditional on a match, a worker is matched with firm j with probability $\left(\frac{v_j}{v}\right)$, where v is the total number of vacancies in the economy and v_j stands for firm j's vacancies. Hence, the value of unemployment $U(\omega, \Omega)$ is given by:

$$U(\omega, \Omega) = b + E\left\{Q\left((1-q)\cdot U(\omega', \Omega') + q \cdot \int_0^1 W_x(\omega', \Omega')\frac{v_x}{v}dx\right)\right\} \tag{5}$$

where $Q = \beta\left(\frac{c'}{c}\right)^{-\sigma}$ is the stochastic discount factor between this and the next period and $W_j(\omega, \Omega)$ is the value of employment at firm j. Meanwhile, employed workers are separated from their job with exogenous probability δ_h, in which case they have to spend at least one period in unemployment before they can be matched with another firm. Following Moscarini and Postel-Vinay (2013), I assume that employed workers can search on the job. In particular, an employed worker at firm j searches with intensity i_j and is matched with another firm with probability $q \cdot i_j$. However, I assume that employed workers only change jobs if they find a firm that offers an equal or better wage. Throughout this paper, I refer to jobs that pay higher wages as *better* jobs.[22] Hence, the value of employment at firm j is given by:

$$\begin{aligned} W_j(\omega, \Omega) = \quad & w_j - \Psi\frac{h_j^{\xi}}{c^{-\sigma}} - \mu\frac{(i_j - \bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h) \\ & + E\{Q((1-\delta_h)(1-q_t i_j)W_j(\omega', \Omega') \\ & + (1-\delta_h)q i_j \int_0^1 max\left\{W_j(\omega', \Omega'), W_x(\omega', \Omega')\right\}\frac{v_x}{v}dx \\ & + \delta_h U(\omega', \Omega'))\} \end{aligned} \tag{6}$$

The first line in equation (6) is the net flow income of a worker employed at firm j. The second term $(\Psi\frac{h_j^{\xi}}{c^{-\sigma}})$ is the value of non-working activities (or the marginal disutility of labor) in terms of consumption, which is derived from the household's utility function (1). The second line in equation (6) says that with probability $(1-\delta_h)(1-qi_j)$ a worker is not exogenously separated

[22]As explained in section 2.3, firms with higher idiosyncratic productivity pay higher wages. Even though firms face decreasing returns to scale, in equilibrium, the ranking of firms' *labor productivity* is identical to the ranking of firms' idiosyncratic productivity.

from firm j and is not matched with another firm. The third line captures that with probability $(1-\delta_h)qi_j$ a worker is not exogenously separated from firm j, is matched with another firm, and picks the firm that gives her the higher continuation value. Finally, with probability δ_h a worker becomes unemployed.

Given that only weakly better jobs are accepted, $max\{W_j(\omega,\Omega), W_x(\omega,\Omega)\} = W_x(\omega,\Omega)\ \forall x \geq j$. Therefore, combining equations (5) and (6):

$$\begin{aligned}
(W_j(\omega,\Omega) - U(\omega,\Omega)) = \quad & w_j - z_j - \mu\frac{(i_j-\bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h) \\
& + E\{Q((1-\delta_h)(1-qi_jF_j)(W_j(\omega',\Omega') - U(\omega',\Omega')) \\
& + (1-\delta_h)qi_jF_j(\tilde{W}_j(\omega',\Omega') - U(\omega',\Omega')) \\
& - q\left(\bar{W}(\omega',\Omega') - U(\omega',\Omega')\right))\}
\end{aligned} \tag{7}$$

Following Hall and Milgrom (2008), I define z_j as the *flow-opportunity cost of employment* for firm j. F_j is the probability of finding a weakly better job than j, $\tilde{W}_j(\omega',\Omega')$ is the expected value of the new job for job changers leaving firm j, and $\bar{W}(\omega',\Omega')$ is the expected value of a new job for unemployed workers. These terms in turn satisfy:

$$z_j = b + \Psi\frac{h_j^{\xi}}{c^{-\sigma}} \tag{8}$$

$$F_j = \int_j^1 \frac{v_x}{v}dx \tag{9}$$

$$\tilde{W}_j(\omega',\Omega') = \int_j^1 W_x(\omega',\Omega')\left(\frac{v_x}{\int_j^1 v_y dy}\right)dx \tag{10}$$

$$\bar{W}(\omega',\Omega') = \int_0^1 W_x(\omega',\Omega')\frac{v_x}{v}dx \tag{11}$$

Notice that the net value of employment $(W_j(\omega,\Omega) - U(\omega,\Omega))$ is a decreasing function in z_j and therefore in consumption. An increase in consumption makes z_j go up and reduces the net value of employment. As a consequence, wages must increase when consumption increases in order to compensate workers for the decline in the value of employment.

Chorodow-Reich and Karabarbounis (2014) find empirically that the flow opportunity cost of employment (z_j) is pro-cyclical and conclude that this procyclicality undermines the results of previous papers attempting to solve the unemployment volatility puzzle. A similar point is made by Brugemann and Moscarini (2010), who argue that rent rigidity, defined as the fraction of wages that do not depend on z_j, can account for at most 20% of the volatility in the job-finding rate. However, notice that in this paper information frictions reduce the sensitivity of z_j to productivity shocks. As explained above, to the extent that aggregate shocks are partially perceived, the household will respond to positive productivity innovations by accumulating capital in an attempt to smooth consumption through time, which prevents z_j from increasing.

Finally, notice that the expectations in equations (5), (6) and (7) are not conditional on the household's information set $\mathcal{I}_h$. Instead, the expectations are conditional on perfect information. This is because equations (5) and (6) describe what a worker will *actually* receive in expectation and not what workers expect to receive. However, workers will have to form expectations about $W_j(\omega, \Omega)$ and $U(\omega, \Omega)$ in order to make search intensity decisions as described in section 2.2.3 and negotiate wages as described in section 2.5.

2.2.3 Search Intensity

I allow search intensity to vary across firms and workers by assuming that, conditional on not being separated from firm j, the cost associated with search intensity i_j is given by $\mu\frac{(i_j-\bar{i})^{1+\epsilon}}{1+\epsilon}$. Therefore, employed workers at firm j choose i_j in order to maximize their expected value $W_j(\omega, \Omega)$. In order to guarantee that employed workers at high-wage firms also have contact with other firms with some probability, I impose the restriction $i_j \geq \bar{i}$ for all j. In other words, it is costless to search with intensity $\bar{i}$.[23] Hence:

$$i_j^* = arg\max_{i_j} \quad E_{\mathcal{I}_h}\{W_j(\omega, \Omega)\} \tag{12}$$

s.t.

$$i_j \geq \bar{i} \tag{13}$$

$$\Omega' = \lambda^h(\Omega) \tag{14}$$

Given this formulation, the optimal value for i_j is given by:

$$i_j^* = max\left\{0, \quad E_{\mathcal{I}_h}\left(\frac{qF_jQ\left(\tilde{W}_j(\omega', \Omega') - W_j(\omega', \Omega')\right)}{\mu}\right)^{\frac{1}{\epsilon}}\right\} + \bar{i} \tag{15}$$

Notice that workers have to form expectations about the value of employment in order to make a search intensity decision. Hence, the optimal value for i_j equates the marginal cost of an additional unit of search intensity ($\mu(i_j - \bar{i})^\epsilon$) with its expected gain ($E_{\mathcal{I}_h}\{qF_jQ\left(\tilde{W}_j(\omega', \Omega') - W_j(\omega', \Omega')\right)\}$). Therefore, if aggregate shocks are partially perceived by workers, the expected gain from search intensity (and as a consequence i_j) become less sensitive to aggregate innovations. This implies that firms do not have to compensate workers as much for the cost of search, making wages

[23] As will become clear, employed workers at high-wage firms gain nothing from changing jobs. Hence, their optimal search intensity will be equal to $\bar{i}$.

less sensitive to aggregate shocks and increasing the sensitivity of unemployment to productivity innovations.

2.3 Firms

There is a continuum of firms indexed by j with a mass normalized to 1. Firms produce with capital and labor, and their output can be used for consumption or for capital accumulation. At the beginning of each period, firms rent capital and open new vacancies, v. A vacancy is matched with a worker with probability $\tilde{q}$. As is standard in the literature, a filled vacancy becomes productive in the subsequent period. However, not all matches become productive. If a vacancy is matched with a worker that is currently employed at a better job, the match is dissolved. Hence, denoting $\tilde{q}^u$ as the probability of filling a vacancy with an unemployed worker and $\tilde{q}^c_j$ as the probability of filling a vacancy with a job changer, the job filling rate for firm j ($\tilde{q}_j$) is given by:

$$\tilde{q}_j = \tilde{q}^u + \tilde{q}^c_j \tag{16}$$

$$\tilde{q}^u = \tilde{q} \cdot \left(\frac{u}{s}\right) \tag{17}$$

$$\tilde{q}^c_j = \tilde{q} \cdot \left(\int_0^j \frac{(1-\delta_h) i_x h_x}{s} dx\right) \tag{18}$$

Notice that $\tilde{q}^u$ is the same for all firms. By contrast, the job filling rate varies across firms even though the probability of a match ($\tilde{q}$) is the same for all firms. $\tilde{q}^c_j$ and $\tilde{q}_j$ are higher for the most productive firms. As a consequence, low-productivity firms rely more on the pool of unemployed workers. Hence, in an expansion, low-wage firms find it more difficult to fill a vacancy and to retain a worker than high-wage firms.

The problem for firm j is given by:

$$\Pi_j(\omega_f, \Omega) = \max_{v_j, k_j} \quad \pi_j + E\left[Q\Pi_j(\omega_f', , \Omega')\right] \tag{19}$$

s.t.

$$\pi_j = y_j - w_j h_j - r k_j - \frac{\kappa}{1+\chi}(\tilde{q}_j v_j)^{1+\chi} \tag{20}$$

$$y_j = e^{a_j + a}\left(k_j^{\alpha} h_j^{1-\alpha}\right)^{\gamma} \tag{21}$$

$$h_j' = (1-\delta_h)(1 - i_j q_t F_j) h_j + \tilde{q}_j v_j \tag{22}$$

$$\Omega' = \lambda^f(\Omega) \tag{23}$$

$$v_j, \quad k_j \geq 0 \tag{24}$$

where a stands for aggregate TFP, which is common to all firms. $\omega_f = \{h_j\}$ is the vector of state variables for firm j, and equation (23) is the perceived law of motion for the economy.

Denoting marginal labor productivity by $p_j = \gamma(1-\alpha)e^{a_j+a}k_j^{\alpha\gamma}h_j^{(1-\alpha)\gamma-1}$, the first order conditions with respect to v_j and k_j are given by:

$$v_j: \quad -\kappa(\tilde{q}_j v_j)^\chi + E\left[Q \cdot J_j'(\omega_f', \Omega')\right] \leq 0 \tag{25}$$

$$k_j: \quad p_j\left(\frac{h_j}{k_j}\right)\left(\frac{\alpha}{1-\alpha}\right) - r = 0 \tag{26}$$

where $J_j(\omega_j, \Omega)$ is the firm's value of an additional worker, or the continuation value of a filled vacancy:

$$J_j(\omega_f, \Omega) = \frac{\partial \Pi_j(\omega_f, \Omega)}{\partial h_j} \tag{27}$$

$$J_j(\omega_f, \Omega) = p_j - w_j + E\left[Q \cdot (1-\delta_h)(1 - i_j q F_j) \cdot J_j(\omega_f', \Omega')\right] \tag{28}$$

Notice that even though the exogenous separation rate δ_h is the same for all firms, the *total* separation rate varies across firms. If we define $\delta_{hj} = 1 - (1-\delta_h)(1 - i_j q_t F_j)$ as firm j's total separation rate, we can see that low-wage (less-productive) firms have higher separation rates. Given that search intensity and F_j are lower for more productive firms, δ_{hj} is also lower for the most productive firms. Note that even though I am not assuming a cost per vacancy posted, labor market conditions affect the value a new vacancy through the firm specific separation rate δ_{hj}. It will be shown that low-wage firms experience a larger increase in separations (quits) in expansions than high-wage firms. Hence, the value of a new worker increases less for less-productive firms in expansions.

2.4 Information Sets

I assume that workers (households) face information frictions in the sense that they do not perfectly know the current value of aggregate TFP (a), which is the only source of aggregate uncertainty. I assume that there is a public signal ($\hat{a}$), based on which workers form expectations. I assume that this public signal is also observed by firms, so that workers' beliefs are common knowledge. The public signal and aggregate productivity are related as follows:

$$\hat{a} = a + n \tag{29}$$

where n is the noise of the signal. The aggregate TFP (a) and the noise (n) are assumed to follow two independent AR(1) processes. I interpret the autocorrelation in this noise as waves of optimism or pessimism:

$$a' = \rho_a \cdot a + e'_a; \quad e_a \sim N(0, \varsigma_a) \tag{30}$$

$$n' = \rho_n \cdot n + e'_n; \quad e_n \sim N(0, \varsigma_n) \tag{31}$$

In order to formally define the equilibrium of this economy and find the solution of this model, I have to assume that workers can perfectly observe the state of the economy with a lag of $\mathcal{T}$ periods where $\mathcal{T}$ is a large integer. Hence, the information set for the representative household is given by:

$$\mathcal{I}_h = \{\hat{a}^{\mathcal{T}}, \Omega_{-\mathcal{T}}\} \tag{32}$$

where $\hat{a}^{\mathcal{T}}$ represents the last $\mathcal{T}$ realizations of $\hat{a}$, and $\Omega_{-\mathcal{T}}$ is the value of the vector Ω $\mathcal{T}$ periods ago. This information set does *not* mean that the representative household does not *perceive* new productivity shocks at all. On the contrary, workers form expectations about current and future economic conditions based on Bayes' rule and this information set, in order to make their decisions. This assumption about information implies that aggregate shocks are partially perceived by workers, who learn slowly about productivity innovations as time elapses while simultaneously continuing to receive positive or negative signals. Hence, if workers do not have enough information to conclude that the economy is in an expansionary path, they will not demand higher wages. Further, partial perception of aggregate shocks causes c, i_j and z_j to become more persistent, another avenue through which wage increases are muted somewhat.

Not surprisingly, empirical evidence suggests that agents do not form expectations based on perfect information. For example, Coibion and Gorodnichenko (2012) find that the expectations of firms, households, and central banks are more consistent with a model in which agents receive noisy signals about aggregate conditions, as is assumed in this paper.

2.5 Wages

I assume that wages are completely flexible and are negotiated at the start of every period according to a simple game, through which firms and workers bargain over the match surplus (S_j):

$$S_j = J_j(\omega_f, \Omega) + W_j(\omega, \Omega) - U(\omega, \Omega) \tag{33}$$

Notice that w_j appears in functions $J_j(\omega_f, \Omega)$ and $W_j(\omega, \Omega)$ in accordance with equations (28) and (6). However, since w_j is an endogenous variable, it is not written an argument for these functions.[24] For expositional purposes, I will abuse notation slightly in this section and define functions $\overrightarrow{J}_j(w, \omega_f, \Omega)$ and $\overrightarrow{W}_j(w, \omega, \Omega)$ as:

$$\begin{aligned}
\overrightarrow{J}_j(w, \omega_f, \Omega) = &\quad p_j - w + E\left[Q \cdot (1-\delta_h)(1 - i_j q F_j) \cdot J_j(\omega_f', \Omega')\right] & (34)\\
\overrightarrow{W}_j(w, \omega, \Omega) = &\quad w - \Psi c^\sigma h_j^\xi - \mu \frac{(i_j - \bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h)\\
&+ E\{Q((1-\delta_h)(1 - q_t i_j Fj)W_j(\omega', \Omega')\\
&+ (1-\delta_h) q i_j F_j \tilde{W}_j(\omega', \Omega') + \delta_h U(\omega', \Omega'))\} & (35)
\end{aligned}$$

Function $\overrightarrow{J}_j(w, \omega_f, \Omega)$ can be interpreted as the value of a filled vacancy for an arbitrary wage w. $\overrightarrow{W}_j(w, \omega, \Omega)$ is interpreted similarly.[25] As a consequence, functions $\overrightarrow{J}_j(w, \omega_f, \Omega)$ and $J_j(w, \omega_f, \Omega)$ are related as follows:

$$J(\omega_f, \Omega) = \overrightarrow{J}_j(w_j, \omega_f, \Omega) \quad (36)$$

$$W(\omega, \Omega) = \overrightarrow{W}_j(w_j, \omega, \Omega) \quad (37)$$

where w_j is the wage that will result from equilibrium.

2.5.1 Wage negotiation

Wages in this economy are negotiated according to the following game:

1. The firm offers a wage x to the worker.

2. The worker observes the firm's offer. Upon acceptance, the game ends with payoffs of $\overrightarrow{W}_j(x, \omega, \Omega) - U(\omega, \Omega)$ to the worker and $\overrightarrow{J}_j(x, \omega_f, \Omega)$ to the firm.

3. If the worker rejects the firm's offer, the match is destroyed with exogenous probability $1 - \vartheta$ (with payoffs to both agents of 0); otherwise, the worker demands a wage y.

4. The firm observes this demand. Upon acceptance, the game ends with payoffs of $\overrightarrow{W}_j(y, \omega, \Omega) - U(\omega, \Omega)$ for worker and $\overrightarrow{J}_j(y, \omega_f, \Omega)$ for firm. If the firm rejects the worker's offer, the game ends with payoffs of zero for both agents.

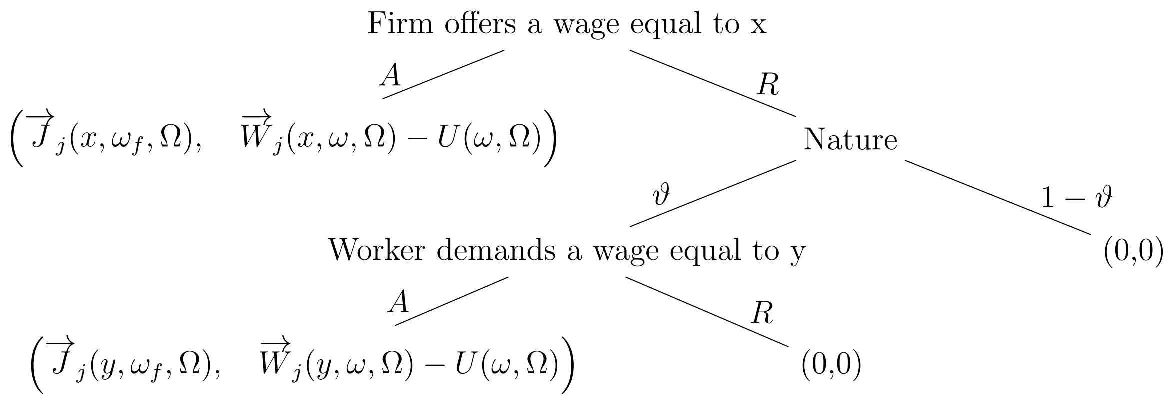
The extensive-from representation of this game is given in Figure 1.

[24] In contrast, the match surplus is independent of w_j.

[25] Notice that I do not index w in equations (34) and (35) by firms j in order to distinguish between an arbitrary wage w and the equilibrium wage w_j. Similarly, i_j in equation (35) refers to the optimal value for search intensity defined in (15). On the other hand, notice that the match surplus does not depend on w:

$$\overrightarrow{J}_j(w, \omega_f, \Omega) + \overrightarrow{W}_j(w, \omega, \Omega) - U(\omega, \Omega) \equiv J_j(\omega_f, \Omega) + W_j(\omega, \Omega) - U(\omega, \Omega) = S_j$$

Figure 1: Wage Determination Game



Note: This figure shows the extensive-form representation of the wage determination game. Firms and workers bargain over the match surplus (S_j) by making wage offers/demands. Details are provided in the text.

2.5.2 Equilibrium Wage and Discussion

Even though this model assumes information frictions, an important benchmark is the case in which all agents have perfect information. In this spirit, the following lemma establishes the equilibrium of this game under perfect information, which will be used to compare the results under information frictions.

Lemma 1. *If all agents in the economy have complete and perfect information, the following strategy profiles constitute the unique sub-game perfect Nash equilibrium of this game:*

- *For the worker:*
  - *To accept only wage offers greater than or equal to x^* where $\overrightarrow{W}_j(x^*,\omega,\Omega) - U(\omega,\Omega) = \vartheta \cdot S_j$*
  - *To demand a wage equal to y^* such that $\overrightarrow{W}_j(y^*,\omega,\Omega) - U(\omega,\Omega) = S_j$ and $\overrightarrow{J}_j(y^*,\omega_f,\Omega) = 0$.*
- *For the firm:*
  - *To offer x^*.*
  - *To accept only wage demands that are less than or equal to y^*.*

Proof. See Appendix B.1 $\square$

Hence, under perfect information, the solution to this game coincides with the solution to the *Nash-Bargaining* game when the worker's bargaining power is equal to ϑ. Therefore, I will call ϑ the *long-term bargaining power* of workers.

Now, before characterizing the solution to this game with information frictions, the following lemmas tell us that, in equilibrium, firms cannot credibly communicate the true state of the economy to the workers.

Lemma 2. *Suppose that agents are information-constrained as described in section 2.4. If there is an equilibrium in which firms' strategy is to reveal the aggregate state of the economy, the best strategy for firms is the same strategy described in Lemma 1.*

Proof. See Appendix B.2 □

Lemma 3. *If agents in the economy are information-constrained as described in section 2.4, then in equilibrium, firms do not follow a strategy in which they perfectly reveal the true state of the economy.*

Proof. See Appendix B.3 □

Even though Lemmas 2 and 3 do not characterize the solution to this game, they make clear that a solution in which firms reveal the true state of the economy is not possible. The intuition is simple: firms have incentives to lie. Firms will always be tempted to tell workers that aggregate productivity is lower than it actually is, so wages can be lower. As a consequence, workers do not rely on firms' offer to form expectations about aggregate conditions. Before defining the solution for this game with information frictions, I make the following assumption:

Assumption 1. *For all realizations of a and $\hat{a}$,*

$$\overrightarrow{J}_j(x^{**}, \omega_f, \Omega) \geq 0 \tag{38}$$

where x^{**} is such that:

$$E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(x^{**}, \omega, \Omega) - U(\omega, \Omega)\right] = \vartheta \cdot E_{\mathcal{I}_h}\left[S_j\right] \tag{39}$$

That is, if both parties agree upon a wage x^{**} such that, according to the worker's information set, a fraction ϑ of the match surplus goes to the worker, the firm still gets a positive payoff for all realizations of the true productivity and the signal. I check that this assumption holds in my calibration. Next, the following lemma presents the solution to this game.

Lemma 4. *If agents in the economy are information-constrained as described in section 2.4, the following strategy profiles constitute a sub-game perfect Nash equilibrium:*

- *For the worker:*

– *To accept only wage offers greater than or equal to x^{**} where:*

$$E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(x^{**},\omega,\Omega) - U(\omega,\Omega)\right] = \vartheta \cdot E_{\mathcal{I}_h}\left[S_j\right]$$

– *To demand a wage equal to y^{**} such that:*

$$E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(y^{**},\omega,\Omega) - U(\omega,\Omega)\right] = E_{\mathcal{I}_h}\left[S_j\right]$$

- *For the firm:*
  – *To offer x^{**}.*
  – *To accept only wage demands that are less than or equal to $\tilde{y}^{**}$ such that $\overrightarrow{J}_j(\tilde{y}^{**},\omega_f,\Omega) = 0$.*

Proof. See Appendix B.4 □

Notice that in equilibrium, wages are a function of what workers would have demanded if given had the chance, even though they do not get to make such a wage demand in equilibrium. This is because, if firms anticipate that workers will ask for a fraction X of their perceived match surplus, they will offer a wage such that workers get $\vartheta \cdot X$ of the match surplus. Notice that this result is common in the literature. In the classical paper of Rubinstein (1982), there are no counter-offers in equilibrium because the first player to move makes an offer that takes into account what the other player would get in the second stage of the game. Similarly, Hall and Milgrom (2008) and Christiano et al (2005) assume that wages are negotiated according to an alternating wage offer game. In those papers, there are no counter-offers in equilibrium because firms compensate workers for what they would get if they had the chance to make a counter-offer.[26] In this sense, this set-up introduces information frictions in a tractable way, and the solution under perfect information of this game is the same as the Nash bargaining solution with workers' bargaining power equal to ϑ.

Regarding the solution with information frictions, Lemma 4 is an important result for this paper. Given that firms have incentives to lie about true productivity (Lemma 3), workers will only use their own information set to assess wage offers. Hence, wage demands will be based on information frictions. To the extent that aggregate TFP shocks are partially perceived, wage demands will be less sensitive to aggregate conditions because workers' expectations are smoother than aggregate shocks. Consequently, wages will be more sluggish under information frictions. Notice that assuming that firms face the same information friction would not affect the solution to this game, and therefore would not affect how sensitive wages are to productivity shocks.

[26] Similarly, Matejka and McKay (2012) derive a model in which goods' prices are determined by consumers' beliefs when they face information frictions and firms have perfect information.

However, if firms observe their overall productivity $(a_j + a)$ at all times in addition to the signal $\hat{a}$ but cannot distinguish between aggregate and idiosyncratic TFP shocks, firms will partially attribute aggregate TFP innovations to idiosyncratic conditions. In that situation, firms will tend to post even more vacancies in expansions because, in addition to the effect of persistent wages, firms will underestimate the increase in separations and the decline in the job filling rate. This case is covered at the end of this paper as an extension.

2.6 Equilibrium

We can now characterize the vector that describes the aggregate state of the economy as $\Omega = \{k, \{h_j\}_{j=0}^1, a^{\mathcal{T}}, \hat{a}^{\mathcal{T}}\}$. As before, $a^{\mathcal{T}}$ and $\hat{a}^{\mathcal{T}}$ refer to the last $\mathcal{T}$ realization of a and $\hat{a}$.

Definition 1. *A recursive competitive equilibrium for this economy is a list of functions* $\{\mathbb{U}(\omega, \Omega)$, $W_j(\omega, \Omega)$, $U(\omega, \Omega)$, $\Pi_j(\omega_f, \Omega)$, $J_j(\omega_f, \Omega)\}$ *[Value Functions],* $\{\{w_j(\Omega)\}_{j=0}^1$, $Q(\Omega)$, $r(\Omega)\}$ *[Prices],* $\{\{i_j(\omega, \Omega)$, $h_j(\omega_f, \Omega)$, $k_j(\omega_f, \Omega)$, $v_j(\omega_f, \Omega)$, $\pi_j(\omega_f, \Omega)$, $\tilde{W}_j(\omega, \Omega)$, $z_j(\Omega)\}_{j=0}^1$, $\bar{W}(\omega, \Omega)$, $c(\omega, \Omega)$, $k(\omega, \Omega)$, $y(\Omega)$, $s(\Omega)$, $\theta(\Omega)\}$*[Allocations],* $\{\{\tilde{q}_j(\Omega)$, $\tilde{q}_j^c(\Omega)$, $F_j(\Omega)\}_{j=0}^1$, $q(\Omega)$, $q^u(\Omega)\}$*[Probabilities], and* $\{\lambda$, λ^f, $\lambda^c\}$*[Law of motion] such that given a law of motion for* $\{\hat{a}$, a, $n\}$*[Exogenous variables]*

- *The representative household and workers optimize: Taking as given prices, probabilities and a perceived law of motion for the economy (3),* $c(\omega, \Omega)$, $k'(\omega, \Omega)$, $i_j(\omega, \Omega)$ *satisfy optimality conditions (4), (15), and the household's budget constraint (2).*

- *Firms optimize: Taking as given prices, probabilities and a perceived law of motion for the economy (23),* $v_j(\omega_f, \Omega)$, $k_j(\omega_f, \Omega)$, *and* $h_j(\omega_f, \Omega)$ *satisfy optimality conditions (25), (26) and the law of motion for* h_j *(57).*

- *Wages and the stochastic discount factor: Wages are a solution to wage bargaining game 2.5.1 and the stochastic discount factor is consistent with* $Q(\Omega) = \beta \left(\frac{c(\omega', \Omega')}{c(\omega, \Omega)}\right)^{-\sigma}$.

- *Consistency of value functions: value functions* $\mathbb{U}(\omega, \Omega)$, $W_j(\omega, \Omega)$, $U(\omega, \Omega)$, $\Pi_j(\omega_f, \Omega)$, *and* $J_j(\omega_f, \Omega)$ *are consistent with equations (1), (6), (5), (19), and (28).*

- *Beliefs: at each point in time, workers' beliefs are determined by their information set* $\mathcal{I}_h$, *their perceived law of motion for the economy (3), and Bayes' rule.*

- *Law of motion: the household's and firms' decision rules imply a law of motion for the economy* (λ) *that is consistent with the household's and firms' perceived law of motion:* $\lambda^f = \lambda^h = \lambda$.

- *Probabilities: probabilities* $\tilde{q}_j(\Omega)$, $\tilde{q}_j^c(\Omega)$, $F_j(\Omega)$, $q^u(\Omega)$, *and* $q(\Omega)$ *are consistent with equation (16), (18), (9), (17) and* $q(\Omega) = m(v(\Omega), s(\Omega))/s(\Omega)$.

- *Allocations:* $\pi_j(\omega_f,\Omega)$, $y_j(\omega_f,\Omega)$, $z_j(\Omega)$, $\tilde{W}_j(\omega,\Omega)$, $\bar{W}(\omega,\Omega)$ *and* $\theta(\Omega)$ *are consistent with equations (20), (21), (8), (10), (11), and* $\theta(\Omega)=\left(\frac{v(\Omega)}{s(\Omega)}\right)$.

- *Aggregation:* v, Y, s, u, k, *are consistent with:*

$$
\begin{aligned}
v(\Omega) &= \int_0^1 v_j(\omega_f,\Omega)dj \\
y(\Omega) &= \int_0^1 y_j(\omega_f,\Omega)dj \\
s(\Omega) &= u(\Omega) + \int_0^1 i_j(\omega,\Omega)h_j(\omega_f,\Omega)dj \\
u(\Omega) &= \int_0^1 (1-h_j(\omega_f,\Omega))dj \\
k(\Omega) &= \int_0^1 k_j(\omega_f,\Omega)dj
\end{aligned}
$$

- *Exogenous variables:* a, $\hat{a}$, *and* n *evolve according to equations (29), (30) and (31).*

Appendix D presents the equations that describe the equilibrium of this economy.

3 Computation

In order to compute the solution to this model numerically, it is important to find and determine a law of motion for the economy, based on which the household forms expectations and makes decisions. This task may not be simple for a large vector Ω, given a distribution of firms. Hence, I solve this model by combining the solution method for heterogeneous agent models proposed by Reiter (2009) and the Kalman Filter, which I used in a previous paper (Morales-Jiménez, 2014). In this section, I explain intuitively the logic behind this method.

First, the Reiter method solves heterogeneous agent models by taking a first-order approximation of the model around the deterministic steady state of the economy.[27] Assume that the following system of equations describes the equilibrium of the economy:

$$f(\Omega,\Omega',\Upsilon,\Upsilon',\mathbb{E})=0 \tag{40}$$

where Υ is the vector of endogenous variables of the economy and $\mathbb{E}$ is the vector of exogenous shocks. The Reiter method then finds the solution in three steps:

1. A finite representation of the economy is provided by discretizing the distribution of agents.

[27] For a detailed application of the Reiter method, see Costain and Nakov (2011).

2. The deterministic steady state of the economy is found by imposing $\mathbb{E} = 0$ and finding the solution to:

$$f^* = f(\Omega^*, \Omega^*, \Upsilon^*, \Upsilon^*, 0) = 0 \tag{41}$$

3. The model is linearized numerically around the steady state, which yields the system of linear equations:

$$f_1^*(\Omega - \Omega^*) + f_2^*(\Omega' - \Omega^*) + f_3^*(\Upsilon - \Upsilon^*) + f_4^*(\Upsilon' - \Upsilon^*) + f_5^* \mathbb{E} = 0 \tag{42}$$

   where f_i^* is the partial derivative of (41) with respect to its *i-th* argument. This system is solved using a standard method such as Sims (2002) or Klein (2000).

Hence, the Reiter method induces a law of motion for the economy of the form:

$$\Omega' = \mathbb{F}\Omega + \mathbb{E} \tag{43}$$

$$\Upsilon = \mathbb{G}\Omega \tag{44}$$

where $\mathbb{F}$ and $\mathbb{G}$ are matrices of coefficients. Therefore, the law of motion for the economy is described by: $\lambda = \{\mathbb{F}, \mathbb{G}\}$. The challenge for a model with information frictions comes from the fact that the law of motion λ is derived from a perceived law of motion λ^h, which in equilibrium has to be equal to the actual law of motion λ.

I exploit the linearity of the Reiter method and proceed as follows:[28]

1. Define a tolerance level.

2. Guess a linear law of motion for the economy $\lambda^{h\{1\}} = \{\mathbb{F}^{h\{1\}}, \mathbb{G}^{h\{1\}}\}$. A good initial guess may be the law of motion of the model under perfect information.

3. Let the household form expectations based on this guess and the Kalman filter.

4. Find the solution of the model using the Reiter method, which is given by a new law of motion $\lambda^{\{1\}} = \{\mathbb{F}^{\{1\}}, \mathbb{G}^{\{1\}}\}$.

5. If the maximum difference between $\lambda^{h\{1\}}$ and $\lambda^{\{1\}}$ is less than the predetermined tolerance level, stop and conclude that $\lambda^{h\{1\}} = \lambda$. Otherwise, update the household's perceived law of

[28]The linearity of the model makes the model tractable as I can compute expectations based on a linear filter. Otherwise, I would need to use non-linear filters (such as the particle filter), which would substantially increase the complexity of the problem for a large vector Ω.

motion as follows:

$$\lambda^{h\{n+1\}} = d \cdot \lambda^{h\{n\}} + (1-d) \cdot \lambda^{\{n\}}; \qquad 0 < d < 1 \tag{45}$$

where d is a fraction that determines how smoothly the guess is updated.

6. Go back to step 3.

4 Quantitative Analysis

In this section, I assess the model's predictions in light of the empirical evidence for the United States for the period 1964 to 2014. Before taking a look at the data, it is important to highlight again two features of the model presented in this paper. First, the main driving force in the model is productivity shocks. As a consequence, it would be incorrect to look only at the unconditional moments in the series, and I should try to identify the fraction of the business cycle that is driven by aggregate productivity shocks.[29] Second, this is a business cycle model. Therefore, I should detrend all U.S. variables in order to make a correct comparison with my model. In order to do that, I follow the literature and filter all series (at quarterly frequency) using the Hodrick-Prescott filter with a smoothing parameter equal to 10^5.[30]

4.1 U.S. Data

I present business cycle statistics for the quarterly time series (seasonally adjusted) of unemployment, vacancies, output, consumption, investment, aggregate TFP, and real wages (deflated by CPI) for job stayers, new hires, job changers and new hires from non-employment.[31] All variables are HP-filtered in logs with a smoothing parameter of 10^5, which is an standard parameter in the literature.

Unemployment is the total number of unemployed people from the *Current Population Survey* (CPS). Vacancies are the composite help-wanted index computed by Barnichon (2010). Output is real output in the nonfarm business sector. Aggregate productivity is measured as the Solow residual as computed by Basu, Fernald, and Kimball (2006), which is available and updated at the

[29] For example, Hall and Milgrom (2008) argue that a significant fraction of unemployment volatility is uncorrelated with productivity, and they estimate that 68% of unemployment volatility is driven by productivity shocks. In their paper, productivity is measured by output per hour. In this paper, I measure productivity as the Solow residual computed by Basu, Fernald, and Kimball (2006). In my model, labor productivity is an endogenous variable, in contrast to TFP, which is the main driving force in the model.

[30] In the last section of this paper, I discuss how my results change if I use a smoothing parameter equal to 1,600. In general my results are not very sensitive to this parameter.

[31] New hires can be decomposed into two groups: new hires coming from unemployment and new hires coming from other jobs (job changers).

website of the Federal Reserve Bank of San Francisco. Consumption consist of non-durable goods and services. Finally, investment is real gross private domestic investment. I include investment as a variable of interest because the impact of the information friction on investment plays an important role in my model.

Given the debate about the cyclicality of wages, I use the CPS microdata to construct the average wage for job stayers, new hires, job changers and new hires from non-employment adjusted for composition effects. In order to compute these wages, I follow Muller (2012) and Haefke et al. (2013) who also used the CPS microdata to construct similar series. Denoting x_{it} as a vector with individual level characteristics such as education, experience, sex, occupation and industry, the wage of individual i at time t (w_{it}) is given by:

$$log(w_{it}) = x'_{it}\beta_x + log(\hat{w}_{it}) \tag{46}$$

where $\hat{w}_{it}$ is the part of wages that does not depend on individual characteristics, which may or may not depend on aggregate conditions. The average wage for group G (w_t^G) adjusted by composition effects is defined as:

$$log(w_t^G) = \sum_{i \in G} log(\hat{w}_{it})\omega_{it} \tag{47}$$

where $G = \{$job stayers, job changers, new hires, new hires from non-employment$\}$, and ω_{it} is the sample weight for individual i, which is provided by the *Bureau of Labor Statistics* (BLS). Since 1994, the CPS has asked individuals whether or not they still work at the same job as in the previous month, making it possible to identify job changers. However, it is not possible to identify job-to-job transitions prior that year. In order to have similar samples, all results regarding wages by groups are restricted to the sample period 1994-2014. Appendix E provides more details about the CPS dataset, the methodology that I follow to construct w_t^G, and some auxiliary regressions and discussion. Given that the literature usually measures wages by the average hourly earnings of production and non-supervisory employees, which is available since 1964, the results for this series can be found in Appendix E as well.

4.2 Business Cycle Statistics and TFP Shocks

Table 1 presents unconditional business cycle statistics for the U.S. economy. As has been previously documented in the literature, unemployment is one of the most volatile series (e.g. Shimer, 2005; Costain & Reiter, 2008). Unemployment is 10 times more volatile than TFP, and 8 times more volatile than output. Similarly, vacancies and the vacancy-unemployment ratio are also highly volatile relative to productivity and output.

Table 1: Business Cycle Statistics: U.S. Economy 1964:Q1- 2014:Q4

		u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
Standard deviation		0.180	0.180	0.348	0.024	0.017	0.096	0.081	0.081	0.087	0.083	0.083	0.018
Autocorrelation		0.960	0.949	0.957	0.941	0.957	0.915	0.211	0.194	0.174	0.234	0.222	0.907
Correlation Matrix	u	1	-0.868	-0.967	-0.832	-0.662	-0.758	0.115	0.112	0.081	0.140	0.131	-0.477
	v		1	0.967	0.781	0.575	0.784	-0.132	-0.134	-0.098	-0.161	-0.151	0.531
	v/u			1	0.834	0.640	0.798	-0.128	-0.127	-0.092	-0.156	-0.145	0.522
	y				1	0.894	0.821	0.168	0.172	0.181	0.148	0.152	0.802
	c					1	0.629	0.310	0.302	0.309	0.299	0.301	0.734
	Inv						1	-0.021	-0.015	0.005	-0.048	-0.040	0.689
	w^a							1	0.993	0.980	0.992	0.993	0.165
	w^s								1	0.973	0.984	0.985	0.171
	w^u									1	0.974	0.982	0.169
	w^c										1	0.999	0.147
	w^n											1	0.151
	a												1

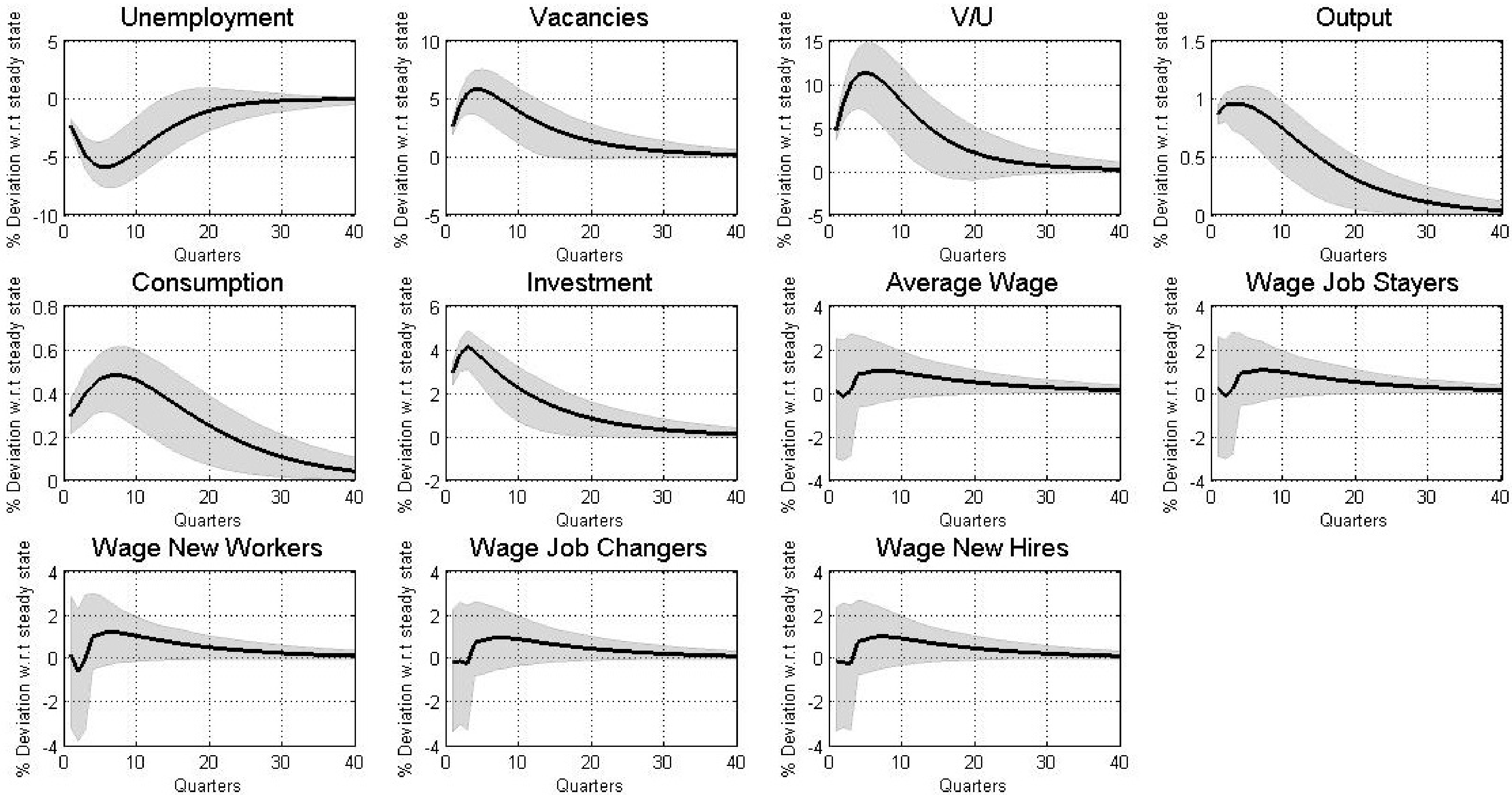
Notes: Statistics for the U.S. economy are based on: u: Unemployment level. v: Help-wanted index (Barnichon, 2010). v/u: Vancancy-unemployment ratio. y: Real output in the nonfarm business sector. c: Consumption of non-durable goods and services. Inv: Real private domestic investment. w^a: Average wage in the economy. w^s: Average wage for job stayers. w^u: Average wage for new workers (workers who were unemployed in the previous period). w^c: Average wage for job changers. w^n: Average wage for new hires (new workers + job changers). a: Solow residual (Basu, Fernald, & Kimball, 2006). All series are seasonally adjusted, logged, and detrended via the HP filter with a smoothing parameter of 100,000.

Table 2: Statistics for Business Cycle Driven by TFP: U.S. Economy 1964:Q1-2014:Q4

		u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
Standard deviation		0.137	0.127	0.254	0.023	0.012	0.083	0.020	0.020	0.023	0.019	0.020	0.017
Autocorrelation		0.972	0.967	0.969	0.953	0.975	0.950	0.962	0.961	0.936	0.949	0.949	0.904
Correlation Matrix	u	1	-0.986	-0.996	-0.960	-0.920	-0.937	-0.857	-0.866	-0.850	-0.811	-0.818	-0.856
	v		1	0.996	0.983	0.926	0.974	0.871	0.879	0.849	0.830	0.834	0.909
	v/u			1	0.972	0.916	0.960	0.888	0.897	0.873	0.842	0.848	0.888
	y				1	0.945	0.976	0.872	0.882	0.856	0.827	0.833	0.942
	c					1	0.861	0.911	0.911	0.897	0.897	0.900	0.790
	Inv						1	0.759	0.774	0.749	0.693	0.703	0.974
	w^a							1	0.999	0.993	0.990	0.992	0.672
	w^s								1	0.990	0.985	0.987	0.695
	w^u									1	0.983	0.988	0.646
	w^c										1	1.000	0.590
	w^n											1	0.598
	a												1

Notes: Statistics for the U.S. economy are based on: *u:* Unemployment level. *v:* Help-wanted index (Barnichon, 2010). *v/u:* Vancancy-unemployment ratio. *y:* Real output in the nonfarm business sector. *c:* Consumption of non-durable goods and services. *Inv:* Real private domestic investment. w^a: Average wage in the economy. w^s: Average wage for job stayers. w^u: Average wage for new workers (workers who were unemployed in the previous period). w^c: Average wage for job changers. w^n: Average wage for new hires (new workers + job changers). *a:* Solow residual (Basu, Fernald, & Kimball, 2006). All series are seasonally adjusted, logged, and detrended via the HP filter with a smoothing parameter of 100,000. These are the business cycle statistics that can be accounted by *TFP* shocks, as described in section 4.2.

Figure 2: Empirical Impulse Responses to a 1% Increase in TFP



Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags, where TFP is assumed to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 10^5. All figures are expressed in percentage points. The x axis represents quarters after the TFP shock. The shaded area represents 95% confidence intervals computed via bootstrap. The sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4.

Since only a fraction of these moments can be accounted for productivity shocks, I follow the literature that investigates the effects of productivity innovations in order to estimate the properties of the business cycle that is driven by TFP shocks.[32] Following Basu et al. (2006) and Gali (1999), I estimate bivariate *near*-VARs. In particular, for each variable x, I estimate the following system of equations:

$$a_t = \alpha_a + \rho_a \cdot a_{t-1} + e_a \tag{48}$$

$$x_t = \alpha_x + \sum_{i=1}^{3} \rho_x^i \cdot x_{t-i} + \sum_{i=0}^{3} \beta_x^i \cdot a_{t-i} + e_{xt} \tag{49}$$

In the first equation, I regress TFP (a) on one lag of itself, which is an hypothesis that cannot be rejected.[33] The second equation regresses each variable x on the current a and three lags of both itself and a.[34] Based on this estimation, I construct recursively the auxiliary variable $\tilde{x}$, which describes how variable x evolves in response to TFP innovations:

$$\tilde{x}_t = x_t \qquad t \leq 3 \tag{50}$$

$$\tilde{x}_t = \alpha_x + \sum_{i=1}^{3} \rho_x^i \cdot \tilde{x}_{t-i} + \sum_{i=0}^{3} \beta_x^i \cdot a_{t-i} \qquad t > 3 \tag{51}$$

Table 2 presents business cycle statistics for these auxiliary variables.[35] As expected, the standard deviations are lower and most of the correlations become stronger. In particular, I estimate that 76% of overall unemployment volatility is due to productivity shocks. Similarly, around 70% of overall volatility in vacancies and the vacancy-unemployment ratio can be explained by TFP. However, productivity does not explain much of the observed volatility in wages. On average, productivity explains 25% of the standard deviation of wages for all groups.

It is important to note that Table 2 reports only the conditional correlations that are induced by TFP shocks. These conditional correlations represent the joint responses of endogenous variables to TFP, not the causal impact of one variable on the other. For example, Table 2 reports a strong, negative and significant conditional correlation between unemployment and wages. That is to say, an increase in wages is associated with a *decrease* in unemployment, which may sound counterintuitive given that firms' labor demand slopes down. However, this is exactly what the model predicts will happen in response to TFP shocks. As it will be shown below, if productivity increases, wages increase because the marginal productivity of labor increases and because firms

[32] Examples in this literature are Barnichon (2010), Basu et al. (2006), Blanchard and Quah (1989), Christiano, Eichenbaum, and Vigfusson (2003, 2005), Gali (1999) and Shea (1998).

[33] Adding further lags does not improve explanatory power.

[34] This number of lags satisfies both the Akaike and Schwarz criteria.

[35] Table 7 in appendix A presents the standard deviation for these moments.

find it more difficult to find and retain new workers. Similarly, unemployment goes down in response to a higher productivity level because firms post more vacancies. Hence, TFP shocks induce a negative correlation between wages and unemployment.

To close this section, Figure 2 plots the Impulse Response Functions (IRFs) of the variables of interest to a 1% increase in aggregate TFP. Given that all of these variables are in logs and HP-filtered, the responses are percentage deviations around a trend and can be interpreted as elasticities. Some results from Figure 2 that will be used to assess my model predictions include: (1) Unemployment, vacancies, and the vacancy-unemployment ratio are very sensitive to TFP shocks. In response to a 1% increase in TFP, unemployment declines 6% while vacancies rise by 7%, which implies that the vacancy-unemployment ratio increases 15%. (2) Responses are hump-shaped, which means that the largest response of these variables does not occur on impact. (3) Wages are positively correlated with TFP when they are adjusted for composition effects. However, wage responses are not statistically significant. (4) On average, wages peak 2 years (8 quarters) after a TFP shock, in contrast to 1 year (4 quarters) for unemployment and vacancies. (5) Wage responses to TFP shocks are very small in absolute value (less than 0.3%) in the first three quarters.

4.3 Parameterization

I calibrate this model to quarterly frequency. I borrow the values for the intertemporal elasticity of substitution (σ), the inverse of the Frisch elasticity (ξ), and the output elasticity of labor (α) from previous literature and set these parameters equal to 1, 0.5, and 0.33.[36] Following the literature, I set ϑ equal to 0.5, which implies equal bargaining power for workers and firms in steady state. γ, which governs the decreasing returns to scale in production, is set to 0.95. The unemployment benefit b is set to 0.041 following the evidence presented by Chodorow-Reich and Karabarbounis (2014).[37] I set δ and β so that the annual depreciation rate is equal to 10% and the annual interest rate is equal to 5% in steady state.

Given firm heterogeneity in this model, it is important to have a matching function that guarantees that all matching probabilities are between 0 and 1, which is not the case for the widely used Cobb-Douglas function. Hence, I follow den Han, Ramey and Watson (2000) and

[36] Peterman (2013) reviews the Frisch elasticities used in macro models (between 2 and 4) and estimates an elasticity for macro studies between 2.9 and 3.1, which implies a value of 0.33 for ξ. In order to have a similar value to the standard literature, I set ξ=0.5, but a lower value would make the results of this paper stronger, as z_j would become less cyclical.

[37] Chodorow-Reich and Karabarbounis (2014) estimate that unemployment benefits are 21.5% of the marginal labor productivity. However, when adjusted by eligibility, claims and take up costs, b declines to 0.041. Given that I will have a distribution of labor productivity, I take a conservative approach, and I set b to 0.041% of the model marginal labor productivity, which is equal to 1.

Hagedorn and Manovskii (2008) and assume the following function:

$$m(u,v) = \frac{uv}{(u^l + v^l)^{\frac{1}{l}}} \tag{52}$$

I choose the parameter l so that the job-finding probability (q) is equal to 0.611 in steady state, which implies an average duration of unemployment equal to 15 weeks consistent with evidence for the US economy. In steady state, the elasticity of matches with respect to vacancies ($\frac{\partial m(u,v)}{\partial v}\frac{v}{m(u,v)}$) is equal to 0.454, which is in the range reported by Petrongolo and Pissarides (2001). The exogenous separation rate δ_h is set such that the unemployment rate is equal to 5.5% in steady state.

I calibrate the distribution of the idiosyncratic TFP (a_j) such that: (1) marginal labor productivity (p_j) is distributed according to a truncated normal between $\left[\underline{p}, \bar{p}\right]$ and (2) the mode of the distribution is 1. Hence, everything is term of the mode (marginal) labor productivity across firms.[38] The standard deviation of the normal distribution is calibrated to 0.2, which is consistent with Long, Dziczek, Luria and Wiarda (2008).[39] Based on the evidence presented by Kahn and McEntarfer (2014), the extreme points of the distribution ($\underline{p}$ and $\bar{p}$) are calibrated such that the wage paid at the most productive firm is 5 times the wage paid at the least productive firm. I discretize the distribution for a_j into 101 points. As to hiring costs, I calibrate the parameter χ to target the autocorrelation of aggregate vacancies, and κ is set such that the total number of employed workers in steady state is equal to 0.945.

I calibrate the disutility of labor parameter Ψ such that the average of the ratio $\frac{z_j}{p_j}$ across firms is equal to 0.72, which is consistent with the value found by Hall and Milgrom (2008).[40] The minimum value for search intensity is calibrated such that the number of job changers per month in steady state is equal to 2.5% of the total population, which is consistent with the estimates of Fallick and Fleischman (2004). Following Gertler, et al. (2014), I set the search cost parameters $\epsilon = 0.9$ and $\mu = 1$.[41] Finally, the persistence of aggregate TFP is calibrated to 0.95 and the standard deviation to 0.018. Following Coibion and Gorodnichenko (2012), σ_n and ρ_n are calibrated such that the persistence of the forecasting error is equal to 0.8 and workers give a weight of 20% to new information. Table 3 summarizes the aforementioned calibration parameters and their sources when appropriate.

[38]Given that the distribution of employment is not uniform in equilibrium, the median productivity across firms is not equal to the median productivity across workers.

[39]They report that the standard deviation of log productivity was 0.657 in 1997, while the median log productivity was 3.47. Hence, as a fraction of the median, the standard deviation is approximately 0.2.

[40]There is an extensive debate surrounding the value of the flow opportunity cost of employment (z) in the literature, with parameterizations ranging from 0.4 (e.g. Shimer, 2005) to 0.955 (e.g. Hagedorn and Manovskii, 2008). A value around 0.72 is less controversial than these extremes.

[41]These values guarantee that i_j is less than 1 for all firms.

Table 3: Parameter Values

Externally Calibrated

Parameter	Value	Description
σ	1	Intertemporal elasticity of substitution
ξ	0.5	Inverse of Frisch elasticity
γ	0.95	Decreasing returns to scale in production function
α	0.33	Labor share in production function
ρ_a	0.95	Persistence of productivity shocks
ς_a	0.018	Standard deviation of productivity shocks
μ	1	Parameter in the cost function of search intensity
ϵ	1	Convexity of cost function of search intensity

Internally Calibrated

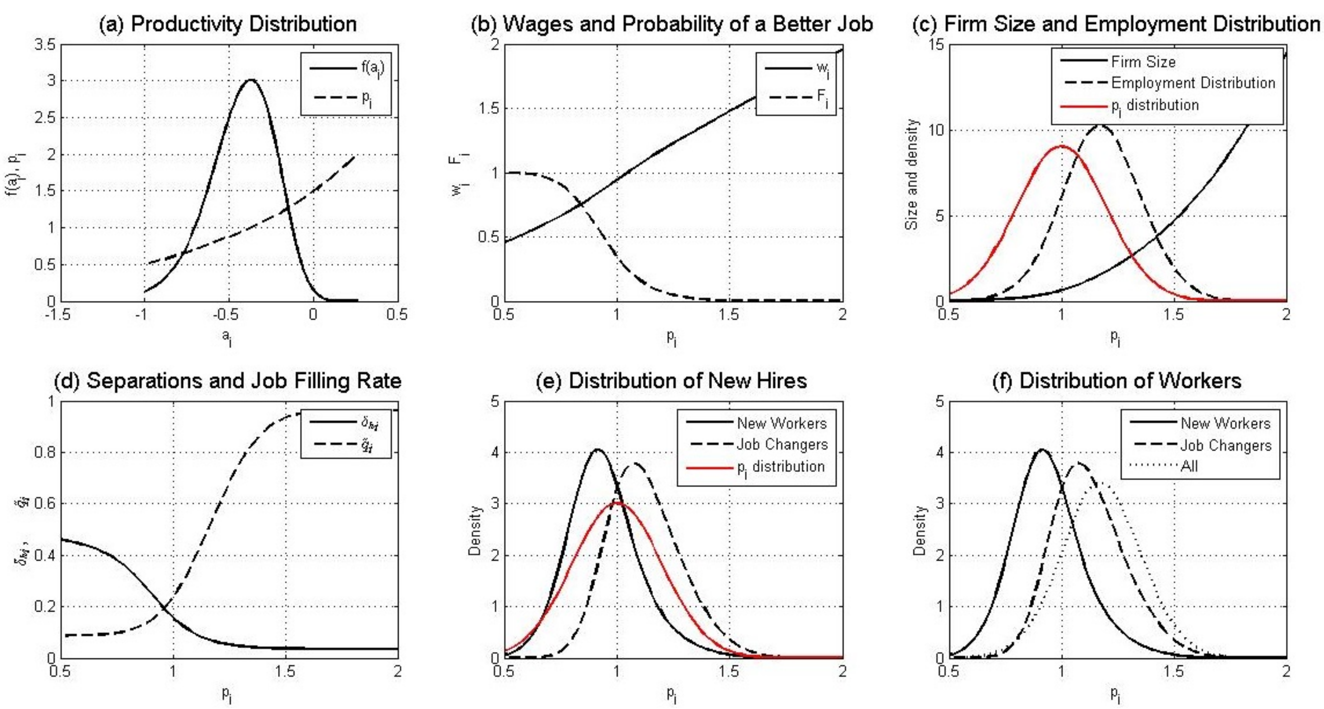
Parameter	Value	Description	Target
a_j		Idiosyncratic TFP distribution	Marginal labor productivity distributed truncated normal with mean 1, standard deviation 0.2 and truncated range (0.5,2).
Ψ	0.8	Desutility of labor parameter	Average $\frac{z_j}{p_j}$ equal to 0.72.
ς_n	$5 \cdot \varsigma_a$	Signaling parameter	Weight on new information = 20%.
δ_h	0.0356	Exogenous separation rate	Unemployment rate= 5.5%
b	0.041	Unemployment benefits	Fraction of b over modal (marginal) labor productivity = 0.041.
ρ_n	0.8	Signaling parameter	Persistence of forecasting error = 0.85.
l	4	Matching function parameter	Unemployment duration $\approx$ 15 weeks.
κ	0.8416	Hiring cost function parameter	Total employment = 0.945.
$\bar{i}$	0.6	Minimum search intensity	Fraction of job changers = 2.5%/month
β	0.9879	Discount factor	Annual interest rate = 5%
χ	0.6	Hiring cost function convexity	Persistence of vacancy index.
δ_k	0.026	Capital depreciation rate	Annual depreciation rate = 10%.

Notes: This table summarizes the parameterization of the model. Details are reported in section 4.3.

4.4 Model versus Data

Before turning to the dynamics, I first present Figure 3, which illustrates the role of heterogeneous firms in this model. Panel (a) plots the distribution of idiosyncratic TFP across firms ($f(a_j)$) and the marginal labor productivity associated with each a_j, and panel (b) shows the wage rate (w_j) and the probability of finding a better job conditional on a match for employed workers (F_j). We can see that the most productive firms have higher marginal labor productivity and as a consequence pay higher wages.[42] Panel (c) shows the average firm size as a function of the firm's labor productivity p (solid black line), and the distributions of employment (dashed line). In particular, the dashed black line in panel (c) plots the fraction of workers that are currently employed in a firm with labor productivity equal to p_j. As in Moscarini and Postel-Vinay (2013) the most productive firms are larger in equilibrium, and therefore the distribution of employment is shifted to the right in comparison with the distribution for p.

Figure 3: Firm and Employment Distribution in Steady State



Note: This figure plots the distributions of employment and productivity across firms in steady state along with the separation rate, job filling rate and wage associated with each firm.

Panel (d) plots the separation rate (δ_{hj}) and the job filling rate ($\tilde{q}_j$) associated with each level of marginal labor productivity. Since employed workers only accept jobs that pay a higher wage and

[42] Even though we may expect a positive relationship between a firm's TFP (a_j) and its marginal labor productivity (p_j), this may not hold under decreasing returns to scale. However, a strictly convex hiring cost function guarantees a positive relationship between a_j and p_j in equilibrium.

unemployed workers always accept a job offer, the most productive firms have a higher job filling rate and a lower separation rate than less-productive firms. This also implies that low-paying firms rely more on the pool of unemployment while high-wage firms find most of their new hires from the pool of employment. Hence, it is not surprising that the labor productivity distribution of new workers (individuals that were unemployed in the previous period) is shifted to the left relative to the productivity distribution of all firms, while the distribution of job changers is shifted to the right (panel (e)) -new workers are more likely to find a job in a low-paying firm, in contrast to job changers, who are poached by the most productive firms.

In panel (f), we can also see that the distribution of overall employment is even more shifted to the right than the distribution of job changers. This is because the most productive firms have a low separation rate in equilibrium. In other words, a firm at the right tail of the productivity distribution has a higher job filling rate but also a lower separation rate than a firm at the middle of the distribution. Hence, a very productive firm doesn't have to post as many vacancies as a firm that is in the middle of the distribution.

Based on these distributions, Table 4 reports the average wage for different types of workers. The average wage for job stayers is higher than for any other group. This is because high-paying firms have the lowest separation rate, which gives a higher weight to employed workers at those firms. In contrast, the average wage for new workers (hired from unemployment) is the lowest among these groups of workers. As explained earlier, new workers are more likely to find a job at a low-paying firm.

Table 4: Average Wages in Steady State

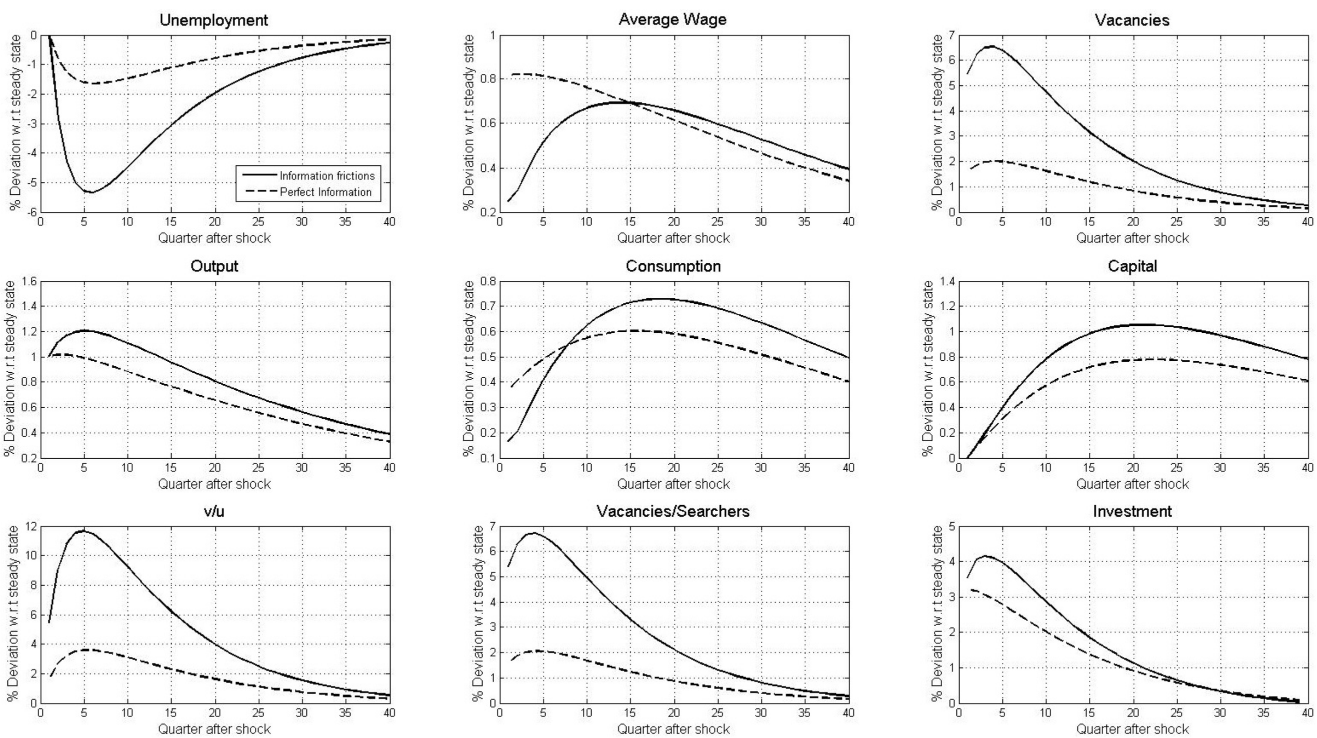
All workers	Job Stayers	New Hires	Job Changers	New Workers
1.1419	1.1563	1.0072	1.0827	0.8776

Notes: This table reports the average wage for different groups of workers in steady state.

Next, Figures 4 and 5 plot the Impulse Response Functions of the aggregate variables of this model to a 1% increase in aggregate TFP (solid black lines). In order to suss out the role of information frictions, I simultaneously plot the IRFs generated by a calibrated model in which agents have perfect information (dashed lines). In addition, Figure 6 plots the IRFs for the 10th, 25th, 50th, 75th, and 90th percentiles of idiosyncratic productivity in the economy.

Based on these figures, we can see the role of information frictions in amplifying the unemployment response to productivity shocks. Since TFP shocks are partially perceived by workers, wages are less sensitive to aggregate productivity innovations (Figure 4). In particular, the assumed information friction has two reinforcing effects on wages. First, workers' expectations are highly sluggish. Hence, in a boom, workers do not demand a large increase in wages because they do not have enough information to conclude that the economy has entered an expansionary path. Second, given workers' beliefs, consumption does not change significantly on impact, so that a large fraction of the increase in aggregate output is absorbed by investment. This curbs the increase of the flow of opportunity cost of employment (z_j) from increasing, which makes wages even less responsive. Therefore, firms have more incentives to expand employment because wages adjust slowly to the true state of the economy.

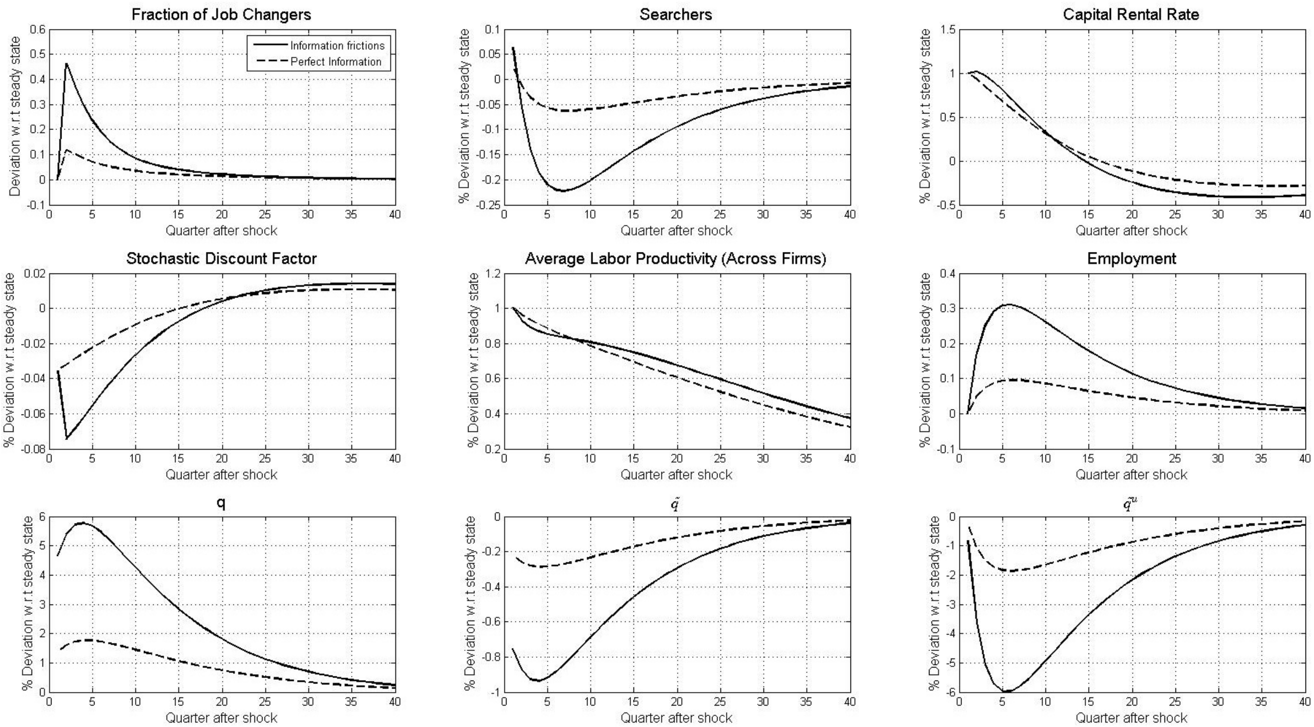
Figure 4: Impulse Response Function to a 1% Increase in Aggregate Productivity



Note: This figure plots model Impulse Response Functions (IRFs) to a 1% increase in aggregate TFP. Solid black lines are the IRFs for a model in which workers face information frictions, and dashed-lines are the IRFs generated by a model in which all agents have perfect information.

However, firms' responses to this shock are not uniform. Actually, only the most productive firms experience an expansion in employment as a consequence of a positive aggregate TFP innovation. Since there is a large expansion in overall employment, there is a large flow of job changers that makes the separation rate increase for low-paying/less-productive firms. Hence, the value of a new hire is affected by two countervailing effects. On the one hand, the productivity increase, combined with sluggish real wages, tends to increase the value of an additional worker for firms in an expansion. On the other hand, an increase in the separation rate reduces the value of an addi-

Figure 5: Impulse Response Function to a 1% Increase in Aggregate Productivity

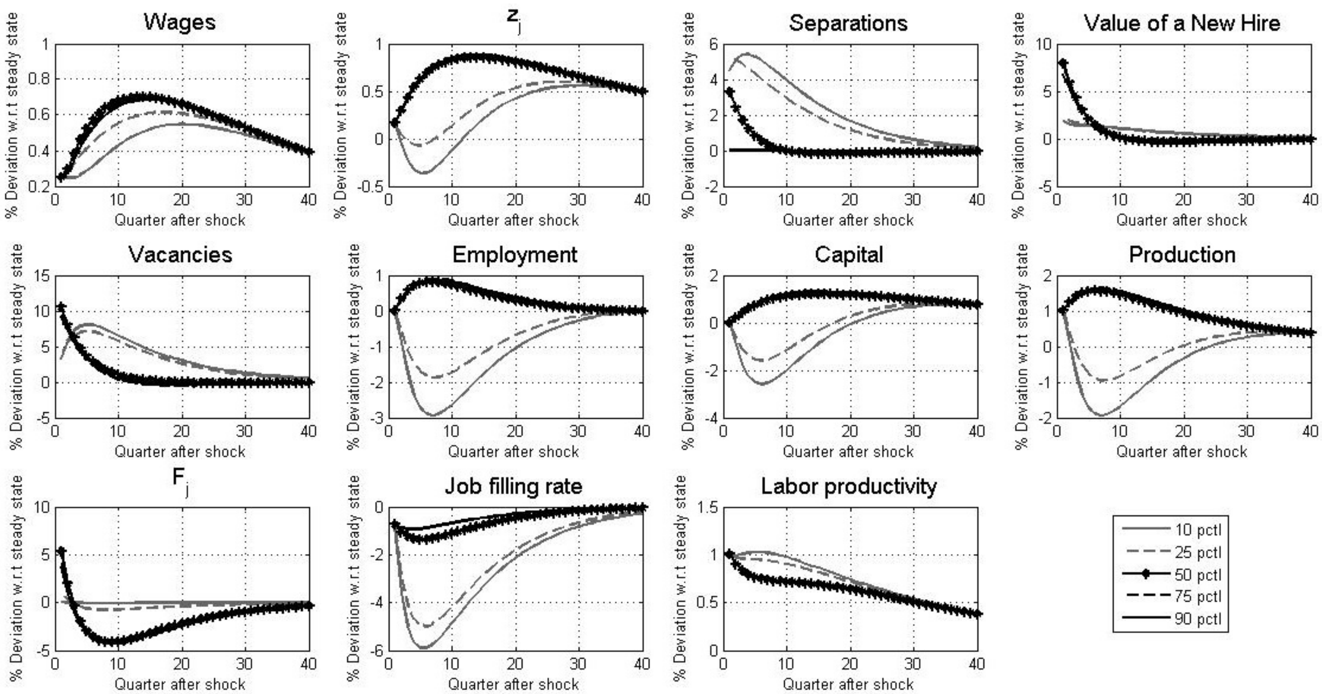


Note: This figure plots model Impulse Response Functions (IRFs) to a 1% increase in aggregate TFP. Solid black lines are the IRFs of a model in which workers face information frictions, and dashed-lines are the IRFs generated by a model in which all agents have perfect information. q, $\tilde{q}$, and $\tilde{q}^u$ denote the job finding rate, the probability that a vacancy is matched with a worker, and the job filling rate (from unemployment), respectively.

tional worker because firms expect the match to not last as long. Hence, the value of an additional worker should increase more for highly-productive firms. Therefore, they expand employment the most. According to these results, the increase in the separation rate for low-paying firms is so large that they reduce their employment levels, as they are crowded out by the large expansion of highly productive firms. This implies that the differential employment growth rate between high and low paying firms is positive and procyclical, which is consistent with the empirical evidence (e.g. Kahn & McEntarfer, 2014; Haltiwanger, et al., 2015).

This differential growth rate in employment implies a differential growth in the flow opportunity cost of employment (z_j). Since high-paying firms are expanding employment the most, they also experience a larger increase in z_j, which makes their wages increase more than the wages for low-paying firms. The fact that wages increase more for the most productive firms does not imply that their workers have more or better information than workers employed at low-paying firms. Since workers can perfectly distinguish among firms and they know that high-productive firms are more sensitive to the business cycle, employees at the most productive firms demand a higher wage than employees at low-productive firms in response to an increase in perceived productivity.

Figure 6: Distributional Dynamics to a 1% Increase in Aggregate Productivity



Note: This figure plots the Impulse Response Functions (IRFs) for a model with information frictions for different firms to a 1% increase in aggregate TFP. Solid gray lines are the IRFs for firms at the 10th percentile of idiosyncratic TFP. The dashed-gray lines are the IRFs for firms at the 25th percentile. The solid x-marked black lines are the IRF for the median firm. The dashed black lines are the IRF for firms at the 75th percentile, and the solid black lines are the IRFs for firms at the 90th percentile. z_j and F_j denote the flow opportunity cost of employment for firm j, and the probability of finding a weakly better job than j, respectively.

Hence, the differential employment growth rate occurs despite the larger adjustment in wages for high-paying firms, which is also consistent with the empirical evidence. Kahn and McEntarfer (2014) do not find that the differential employment growth rate is driven by high-paying firms facing more sluggish wages. In fact, they show that high-paying firms reduce wages in recessions relative to low-paying firms.

These results imply different dynamics for the job-filling rate across firms ($\tilde{q}_j$). In particular, since low-paying firms rely more on hiring from the pool of unemployment, they experience a large decline in $\tilde{q}_j$ because of the decline in unemployment. By contrast, high-paying firms experience an initial decrease in the job-filling rate because of the large increase in the total number of vacancies. But as the pool of employment increases, the job filling rate for the most productive firms goes up because most of their new hires come from other firms.

Table 5 reports the business cycle statistics generated by a model in which workers face information frictions. In particular, I simulate the model for 100,000 periods and detrend all variables using the HP filter with a smoothing parameter of 10^5. To facilitate comparison, Table 9 in Appendix A compares the business cycle moments generated by my model and those obtained from the data. Based on my simulations, we can see that a model in which workers face information frictions is able to explain 60% of the overall volatility of unemployment and around 70% of the overall volatility in other labor market quantities. Compared to my empirical estimates, my model is able to explain 90% of the unemployment volatility that is attributable to TFP shocks. Similarly, my model does a good job in terms of correlations, as the correlations predicted by the model are very close to those derived from the data. It is also worth noting that my empirical exercise helps us to reconcile some empirical inconsistencies of the search and matching model described in Hagedorn and Manovskii (2011). In particular, they argue that the contemporaneous correlation between the vacancy-unemployment ratio and productivity is significantly lower in the data than in the model and that the standard deviation of wages is higher than the wage elasticity with respect to productivity. According to my empirical analysis, conditioning on TFP shocks in the data increases the contemporaneous correlation between the vacancy-unemployment ratio and TFP from 0.52 to 0.89 and reduces the standard deviation of wages from 0.08 to 0.02. My calibrated model generates a correlation between the vacancy unemployment ratio and TFP equal to 0.93 and a standard deviation of wages around 0.013.[43]

Figure 7 compares the IRFs estimated from the data with those generated by the model. With the exception of the IRFs for output and consumption, the model is able to explain very well the dynamics of these variables after a productivity shock. Even though the IRF for output predicted by the model does not lie in the confidence interval, the model is able to predict a hump-shaped response. It is worth noting that, by construction, the model must predict an impact response equal to 1%. On the other hand, even though my model predicts too large consumption response, it is worth noting that a calibrated model with perfect information shares this flaw. Also, notice that a smaller consumption response (as in the data) would reinforce my results on wages and unemployment, as the increase in the opportunity cost of employment would be smaller (less cyclical). On the other hand, the model with information frictions does a good job explaining the dynamics of both wages and investment. Recall that the real part of the information friction plays an important role in this model. Given that aggregate shocks are partially perceived by workers, most of the shock is absorbed by investment (capital accumulation). These IRFs tell us that the model does a good job of explaining the behavior of investment, as my model predicts investment responses that mimic very well the IRF estimated from the data.

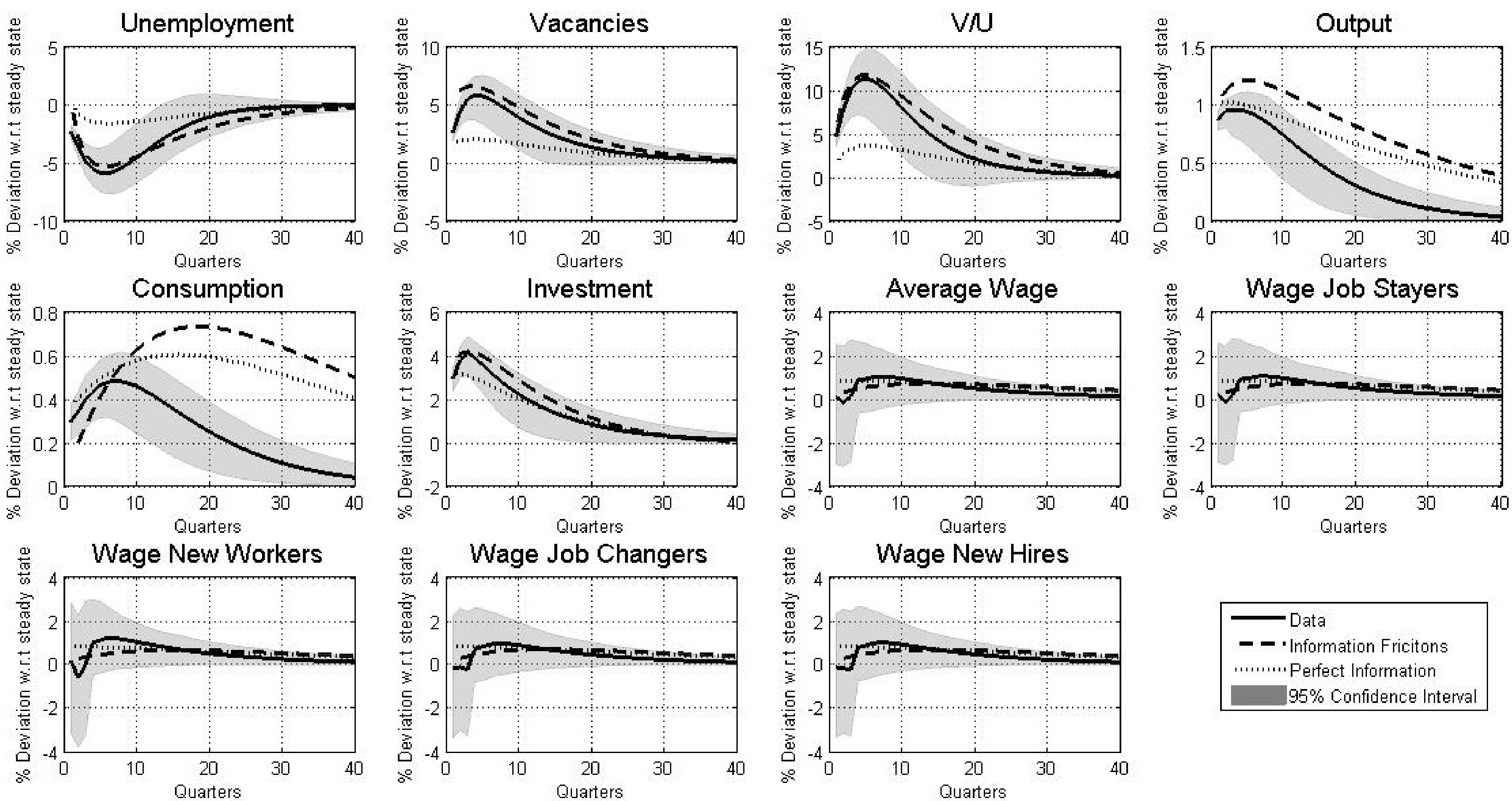
[43] Hagedorn and Manovskii (2011) also discuss an additional shortcoming: the correlation between vacancies and productivity is maximized when vacancies are led one or two quarters. My model is consistent with this fact. However, this is because I assume a strictly convex hiring cost function. Gertler and Trigari (2009) are also able to generate this pattern by assuming a quadratic adjustment cost in employment.

Table 5: Simulated Business Cycle

		u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
Standard deviation		0.113	0.160	0.259	0.024	0.013	0.089	0.013	0.013	0.013	0.013	0.013	0.017
Autocorrelation		0.960	0.925	0.960	0.934	0.989	0.926	0.981	0.981	0.979	0.981	0.980	0.871
Correlation Matrix	u	1	-0.799	-0.928	-0.885	-0.560	-0.839	-0.737	-0.739	-0.685	-0.733	-0.725	-0.812
	v		1	0.965	0.903	0.420	0.983	0.619	0.619	0.616	0.630	0.626	0.932
	v/u			1	0.943	0.503	0.972	0.703	0.704	0.679	0.708	0.702	0.929
	y				1	0.695	0.927	0.849	0.849	0.824	0.849	0.844	0.955
	c					1	0.400	0.966	0.966	0.964	0.964	0.964	0.970
	Inv						1	0.613	0.613	0.592	0.618	0.611	0.472
	w^a							1	1.000	0.987	0.998	0.996	0.662
	w^s								1	0.986	0.998	0.996	0.663
	w^u									1	0.993	0.996	0.637
	w^c										1	0.999	0.663
	w^n											1	0.657
	a												1

Notes: Statistics for the simulated economy under information frictions: *u:* Unemployment level. *v:* Vacancies *v/u:* Vancancy-unemployment ratio. *y:* Output. *c:* Consumption. *Inv:* Investment. *w^a:* Average wage in the economy. *w^s:* Average wage for job stayers. *w^u:* Average wage for new workers (workers who were unemployed in the previous period). *w^c:* Average wage for job changers. *w^n:* Average wage for new hires (new workers + job changers). *a:* Aggregate TFP. All series are seasonally adjusted, logged, and detrended with the HP filter with a smoothing parameter of 100,000.

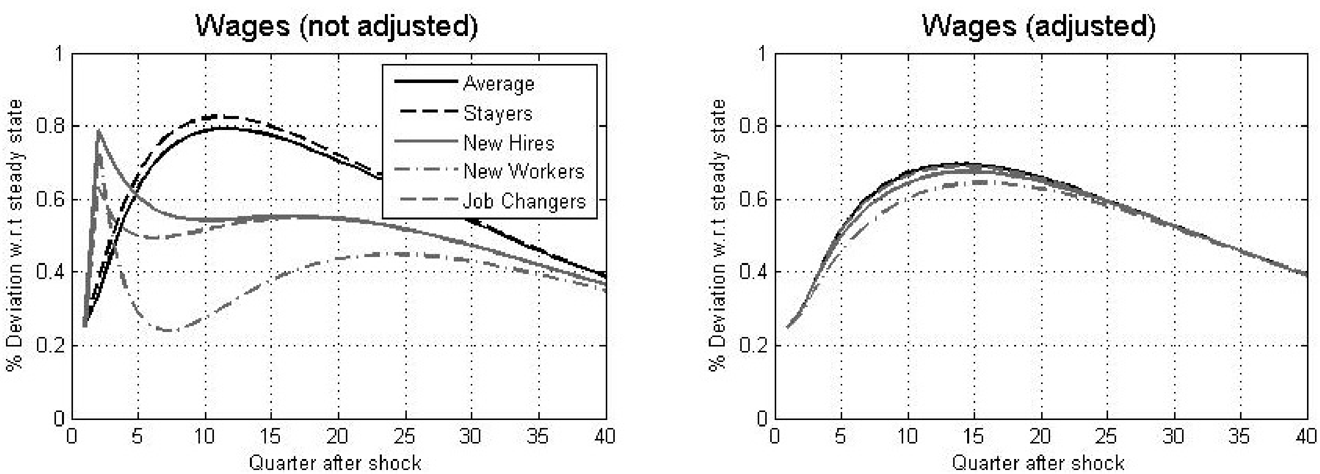
Figure 7: IRFs to 1% Increase in Aggregate Productivity
Data versus Model



Note: The solid black lines in this figure plot the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags, where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 10^5. All figures are expressed in percentage points. The x axis represents quarters after the TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. The sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4. The dashed lines are the IRFs generated by a model with information frictions, and the dotted lines are the IRFs generated by a model in which all agents have perfect information.

Finally, the left panel of Figure 8 plots the IRF for average wages for each type of worker in my benchmark model. Notice that the average wage for new hires, job changers and new workers have a larger response on impact than the average wage for job stayers and all workers. However, these differences are driven primarily by heterogeneity across firms. To see this, note that average wages increase for two reasons: (1) because wages within firms increase and (2) because high-wage firms increase employment the most in an expansion. In order to see how important these two effects are, the right panel of Figure 8 plots the average wage for all groups of workers when wages are adjusted for this composition effect. In particular, I follow Horrace and Oaxaga (2001) and define the average wage for group G adjusted for composition effects ($\tilde{w}^G$) as the average wage for a fixed composition of workers across firms, where the composition of workers is given by the disribution of workers across firms in steady state.

Figure 8: Wages Responses to a 1% Increase in Aggregate Productivity



Note: This figure plots the evolution of the average wage for different groups of workers in response to a 1% increase in aggregate productivity. The left panel plots the evolution of average wages not adjusted for composition effects. The right panel plots the evolution of average wages adjusted for composition effects.

By comparing the two panels of Figure 8, we can infer that the initial increase in the wages of new hires, job changers and new workers is due almost entirely to the large increase in employment at high-paying firms. However, when I control for the fact that high wage firms expand employment the most, wages of all groups have the same behavior -wage responses to aggregate shocks are gradual. Similarly, when controlling for this composition effect, there are not significant differences in wage responses for different groups of workers. This result is in line with previous empirical evidence. For example, using the National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID), Hagedorn and Manovskii (2013) find no significant differences in the cyclicality of wages for job changers and job stayers when they control for match quality.[44]

How does the wage flexibility in my model compare to the data? Pissarides (2009) finds that the wage semi-elasticity with respect to the unemployment rate for job changers is around -3% in comparison for -1% for job stayers.[45] This evidence has been cited by Pissarides and others in favor of models with flexible wages and against models with sticky wages. In order to estimate this semi-elasticity in my model, I simulated the model for 100,000 periods, computed the average wages for all groups adjusted for composition effects and ran the following regression for each group:

$$log(\tilde{w}_t^G) = \alpha_0 + \beta_u \cdot ur_t + e_t \tag{53}$$

where $\tilde{w}_t^G$ is the average wage (adjusted for composition effects) for group G.[46] α_0 is a constant, ur_t is the unemployment rate at time t, e_t is an error term, and β_u is the wage semi-elasticity with respect to the unemployment rate.

Table 6: Wage Elasticities With Respect To Unemployment

New Hires	Job Changers	New Workers
-3.08	-3.11	-2.97

Notes: This table presents the wage semi-elasticities with respect to the unemployment rate generated by this model. Wages are adjusted for composition effects following the methodology of Horrace and Oaxaga (2001).

This semi-elasticity is reported in Table 6 for new hires, job changers, and new workers. It is worth noting that these values are not a target in my calibration, but we can see that they are all around -3%. That is, this model is robust to the Pissarides critique. In my model, wages for new hires are flexible, and wage semi-elasticities with respect to the unemployment rate are around -3%. If these semi-elasticities were lower (in absolute terms) than -3%, as argued by Gertler et al. (2014), my model predictions would be reinforced as wages would be less cyclical, which would further increase firms' incentives to expand employment.

[44] Gertler et al. (2014) find the same result for a different sample period using the Survey of Income and Program Participation (SIPP) dataset. Below, I discuss the consequences of assuming sticky wages for job stayers.

[45] These numbers imply that an increase of one percentage point in unemployment (for example, from 5 to 6%) makes wages for job changers and job stayers decrease by 3% and 1%, respectively.

[46] As before, I control for composition effects following the methodology of Horrace and Oaxaga (2001). The advantage of this methodology, in contrast to running a regression with firm dummies, is that the results are independent of the excluded variable. Haefke et al. (2013) also discuss the advantages of this methodology when constructing the average wage for new workers (production and non-supervisory employees).

5 Robustness

This section addresses the robustness of my results to variations in some of the assumptions that underlie my analysis. In particular, I will consider: (1) allowing sticky wages for job stayers, (2) allowing firms to face information frictions, (3) allowing a different HP smoothing parameter in the data, and (4) allowing for a positive probability of workers changing to an inferior match.

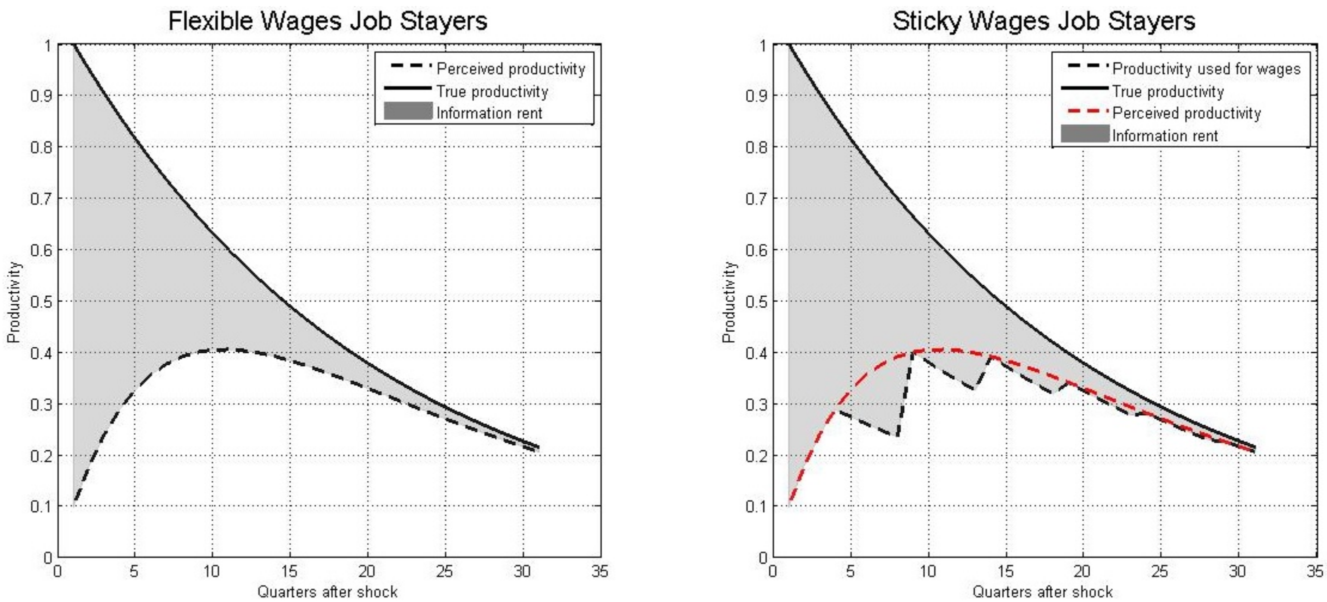
I show that: (1) In contrast to previous literature, assuming that wages for job stayers are sticky amplifies the unemployment response to productivity shocks. When workers negotiate wages for the following n periods, they give up using the flow of information that they would otherwise receive for the next n periods, which makes wages even more sluggish. (2) Assuming that firms face information frictions reinforces my results, as firms underestimate the cost of recruiting new workers in expansions and expand employment even more. (3) Using a smoothing parameter equal to 1,600 makes wages less cyclical in the data and does not have a significant impact on other variables. (4) Assuming that workers move to an inferior job with an exogenous probability does not have a significant impact on my baseline results.

5.1 Sticky Wages for Job Stayers

In contrast to previous literature in which the wage of job stayers is irrelevant for vacancy decisions, assuming sticky wages for continuing workers amplifies the unemployment response to productivity shocks in my model. If a worker has to negotiate her wage for the following n periods, she gives up using the new information she otherwise would be using in the future. To see this clearly, suppose that workers observe everything with a lag of 2 periods. In other words, if the economy is shocked at time t, workers do not know about this shock until period $t + 2$. Hence, if a worker has to negotiate her wage at time t for the following 4 periods and there is a positive productivity shock at time t, she will not demand a higher wage for the following 4 periods because she doesn't know about the productivity shock yet. At time $t + 2$, workers will know about the productivity shock and would like to demand higher wages, but they cannot because their wages are fixed for at least another 2 periods. Given that firms have perfect information, they anticipate that they will keep a large fraction of the match surplus for the following 4 periods, which will in turn create more incentives to post vacancies.

Figure 9 illustrates this point in the case of a positive productivity shock of 1%. The left panel illustrates the evolution of the true productivity (solid black line) and the perceived productivity by workers at each point in time (dashed line), which is derived from the Kalman Filter. Hence, if wages for job stayers are flexible, continuing workers will negotiate wages each period based on their perceived productivity level. Hence, we can define the difference between the solid and dashed lines (gray area) as the information rent that firms capture. This is because firms are producing according to a productivity that is equal to the solid line but are paying labor as if productivity was equal to the dashed line.

Figure 9: Flexible versus Sticky Wages for Job Stayers



Note: This figure illustrates the amplifying effects of sticky wages for job stayers. The left panel plots a situation in which job stayers negotiate their wages every period. The right panel plots the situation of an unemployed worker who finds a job 4 quarters after a TFP shock, when job stayers negotiate their wages every 4 periods and new hires negotiate their wages when they are matched with a firm.

Now, suppose that workers negotiate their wages every 4 periods and new hires negotiate their wages when they are matched with a firm. In this case, workers must form expectations about future economic conditions based on their beliefs about the current state of the economy. The right panel of Figure 9 illustrates the case of an unemployed worker, who finds a job 4 periods after the productivity shock. The red dashed line is workers' perceived productivity at each point in time. For example, in period 4, when the unemployed worker finds a job, she thinks that the true productivity is equal to 0.3. Given that she has to negotiate her wage for the following 4 periods, she forecasts future economic conditions based on her beliefs. Hence, she negotiates wages as if productivity was evolving as in the black dashed line in the right panel of Figure 9. For example, as of period 4, the worker forecasts a productivity equal to 0.22 in period 8 and negotiates wages accordingly. When period 8 actually arrives, the worker has received new information and perceives that aggregate TFP is equal to 0.4, but she cannot renegotiate her wage. Hence, the information rent for firms increases, giving firms more incentives to expand employment. Figure 10 in Appendix A plots the IRFs of this model when wages for new hires are flexible but are negotiated only once annually (every 4 quarters) thereafter.[47] Even though the difference with respect to my baseline model is small, the difference it not insignificant. In particular, the model with sticky wages for job stayers captures very well the dynamics of unemployment for the first 10 quarters and has a larger vacancy response.

5.2 Firms Face Information Frictions

Assuming that firms as well as workers face information frictions reinforces my results. Suppose assume that firms observe their overall productivity $(a_j + a)$ at all times but cannot decompose unexpected changes into aggregate and idiosyncratic shocks. Hence, if firms and workers form expectations about aggregate conditions based on the signal $\hat{a}$, firms will partially attribute aggregate shocks to idiosyncratic conditions. Therefore, in response to aggregate innovations, firms will underestimate the increase in quits and future wage changes that will result from a positive TFP shock. This increases firms' incentives to post more vacancies, as their perceived value of an additional worker is greater than is the actual value.

Figure 11 in Appendix A plots the impulse response functions generated by this model when I allow the information friction to affect firms as well as workers, holding other the model parameters at their benchmark values. As expected, introducing information frictions on the firms side reinforces my results, as the IRFs for labor market quantities are larger than in the benchmark model. Figure 12 in Appendix A plots the IRFs when I re-calibrate the model parameters, and Table 8 in Appendix A presents the simulated business cycle moments. In this new set-up, the main results do not change relative to benchmark results. The unemployment response to productivity shocks is large and wage responses are delayed. However, the responses tend to peak earlier than predicted by my empirical estimates. In terms of business cycle moments, the model in which both firms and workers face information frictions does a good job in terms of standard deviations and correlations. However, the autocorrelation of the labor market quantities become smaller. This is because, on impact, firms overreact to aggregate shocks, and they compensate for this in later periods when they have amassed more information. For example, in response to a positive TFP shock, firms post a lot of vacancies on impact, but they reduce the number of vacancies (post less) as they learn about aggregate conditions and realize that the value of an additional worker is not as high as they had thought. This does not happen when firms have perfect information, as they perfectly predict the value of an additional worker and the convexity of the hiring cost function induces firms to smooth the number of vacancies they post.

[47]This implies that, in each period, a fraction of continuing workers and all new hires will be negotiating their wages for the following 4 quarters.

5.3 HP Filter

For my benchmark empirical results, I detrend the data using the HP filter with a smoothing parameter equal to 10^5. However, it is common in macroeconomics to use a smoothing parameter equal to 1,600 for quarterly data. Figure 13 in Appendix A plots the IRFs of my model along with those estimated using a smoothing parameter equal to 1,600. Responses for labor market quantities, output and investment are not substantially different from those reported in Figure 2. However, the wage responses are less cyclical in the sense that the maximum responses are smaller and less significant, indicating that wage responses to transitory TFP shocks are weak. Why do the wage responses change with the smoothing parameter? On the one hand, we expect wages and productivity to be correlated in the long run. If there is a permanent increase in TFP, we should expect higher wages in the economy. However, whether and how wages adjust to purely transitory shocks is not clear. Hence, the smaller the smoothing parameter we use, the smaller the fluctuations that can be explained by transitory shocks since larger fluctuations are attributed to a long run trend. However, it is worth noting that less cyclical wages in the data favor *wage stickiness* as a driving force of the business cycle. Therefore, my baseline smoothing parameter is conservative in the sense that it reduces the evidence for wage stickiness.

5.4 Probability of Moving to an Inferior Job

In reality we observe job changers that move to lower paying jobs. To the best of my knowledge, there is little research indicating the magnitude of this flow of workers. However, if we assume that such transitions are due to exogenous factors, we can introduce flows of workers to inferior jobs by assuming that, conditional an an inferior match, a worker will switch jobs with exogenous probability Ξ. I ran experiments assuming that Ξ was equal to 0.05 and 0.1 (5 and 10%) and did not find any significant differences from the benchmark model results; details are available on request.

6 Conclusion

I propose a new mechanism for sluggish wages based on workers' noisy information about the state of the economy. In my model, workers receive noisy signals about the current state of the economy and learn slowly about aggregate conditions. Hence, wages do not immediately respond to a positive aggregate shock because workers do not (yet) have enough information to demand higher wages. This delayed adjustment in wages increases firms' incentives to post more vacancies, making unemployment more volatile and sensitive to aggregate shocks. My calibrated model is able to explain 60% of the overall unemployment volatility and displays unemployment and wage dynamics consistent with the data. I find that the unemployment response to TFP shocks is large and hump-shaped, peaking after one year. In contrast, wage responses are delayed and weak, peaking instead after two years.

My model is robust to two major critiques of existing theories of sluggish wages and volatile unemployment: the flexibility of wages for new hires and the cyclicality of the opportunity cost of employment. On the one hand, my model assumes flexible wages for new hires and generates a wage semi-elasticity with respect to the unemployment rate for new hires equal to -3%, which is similar to the estimate of Pissarides (2009) and larger than the estimates of Hagedorn and Manovskii (2013) and Gertler et al (2014). On the other hand, my model predicts a very pro-cyclical opportunity cost of employment, as the value of non-working activities in terms of consumption increases in expansions.

Consistent with recent empirical evidence (e.g. Kahn & McEntarfer, 2014; Haltiwanger et al., 2015), my model predicts that high-wage highly productive firms expand employment more than low-wage firms and also exhibit larger wage adjustments in expansions. This implies that the distribution of new hires shifts to the most productive and high paying firms in response to positive productivity shocks. This has important consequences for new hires, as they find more and better paying jobs in expansions.

In this paper, I examine the data for the United States and estimate the fraction of business cycle moments that can be attributed to productivity shocks. In order to allow for differences in the cyclicality of wages for job stayers and new hires, I use the Current Population Survey to construct average wages for these groups of workers controlling for composition effects. According to my results, between 70 and 75% of the overall volatility in labor market quantities such as unemployment and vacancies can be attributed to transitory TFP innovations. In contrast, only 25% of the overall volatility in wages can be explained by transitory productivity innovations. I find significant and hump-shaped Impulse Response Functions (IRFs) to productivity shocks for unemployment, vacancies and the vacancy-unemployment ratio. These responses peak 4 quarters after the shock, and imply that a 1% TFP shock reduces unemployment by 6%, increases vacancies by 7% and increases the vacancy-unemployment ratio by 15%. By contrast, the IRFs for wages are weak and delayed. A 1% TFP shock increases wages by 1% after 8 quarters. My model is able to reproduce the dynamics that I estimate in the data and is able to explain 90% of the unemployment and vacancy volatility that is due to transitory productivity shocks.

In the robustness section, I show that assuming sticky wages for job stayers increases the unemployment response to productivity shocks. This result is in sharp contrast to existing studies, in which wage stickiness for incumbent workers is irrelevant for hiring decisions as long as wages for new hires are flexible. In my model, if a new hire has to negotiate her wage for the subsequent n periods, she gives up using the new information that she otherwise would be using in the future, which will reduce the gap between the wage she actually demands and the wage she should be demanding. Therefore, if wages for new hires do not initially adjust to an aggregate shock (because of the information friction), sticky wages for job stayers increase the time it will take for a worker's wage to adjust, which further increases firms' incentives to increase employment in expansions.

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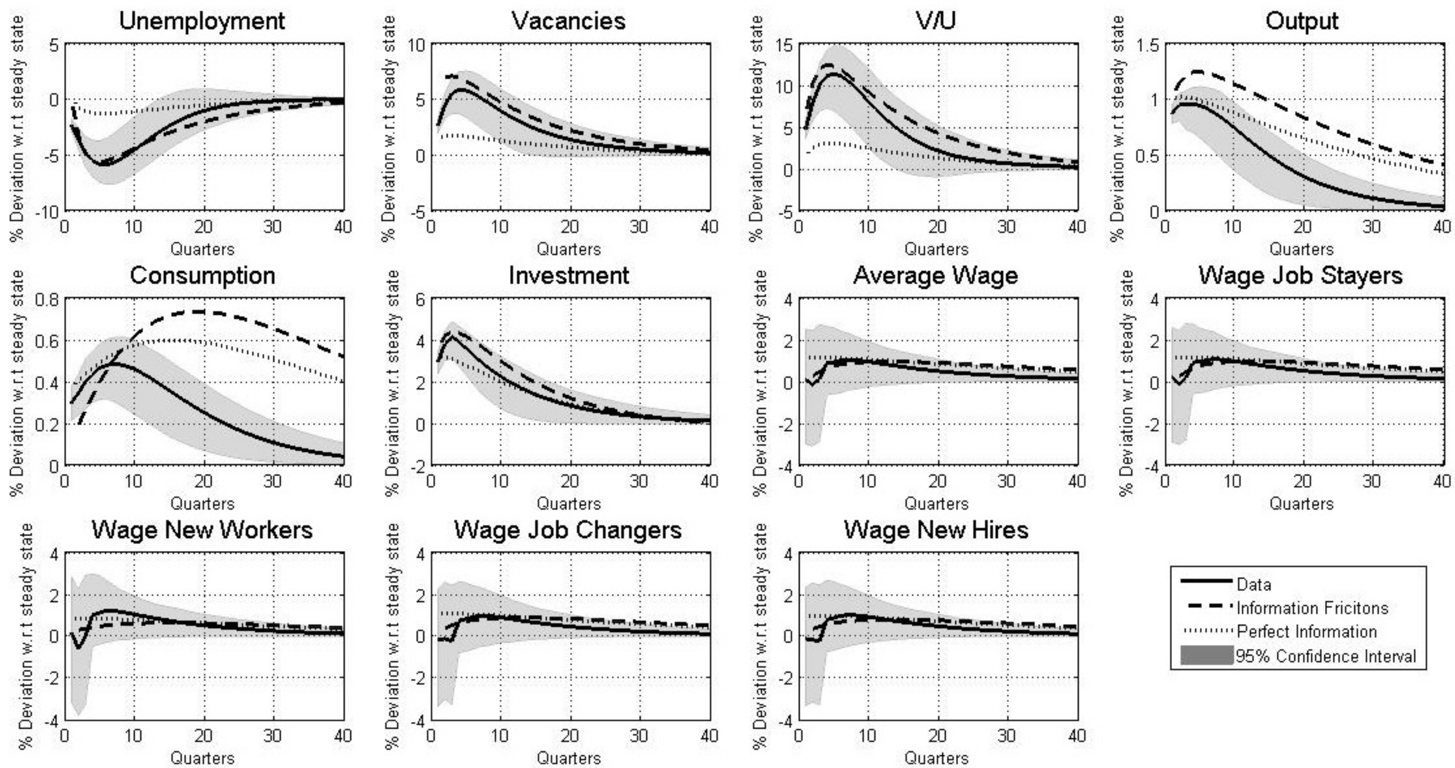
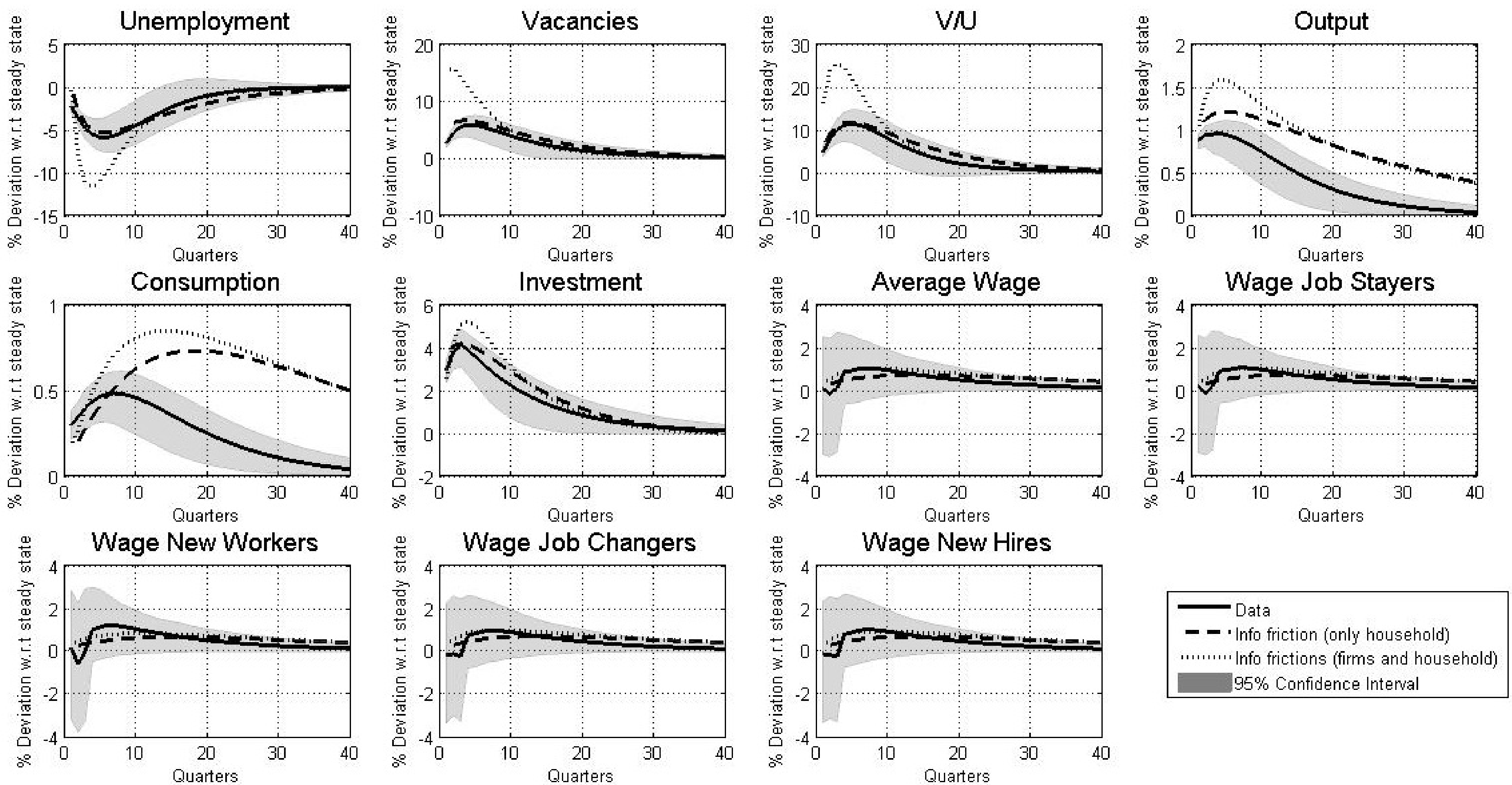
A Other Figures and Tables

Figure 10: IRFs to 1% Increase in Aggregate Productivity
Data versus Model with Sticky Wages for Job Stayers



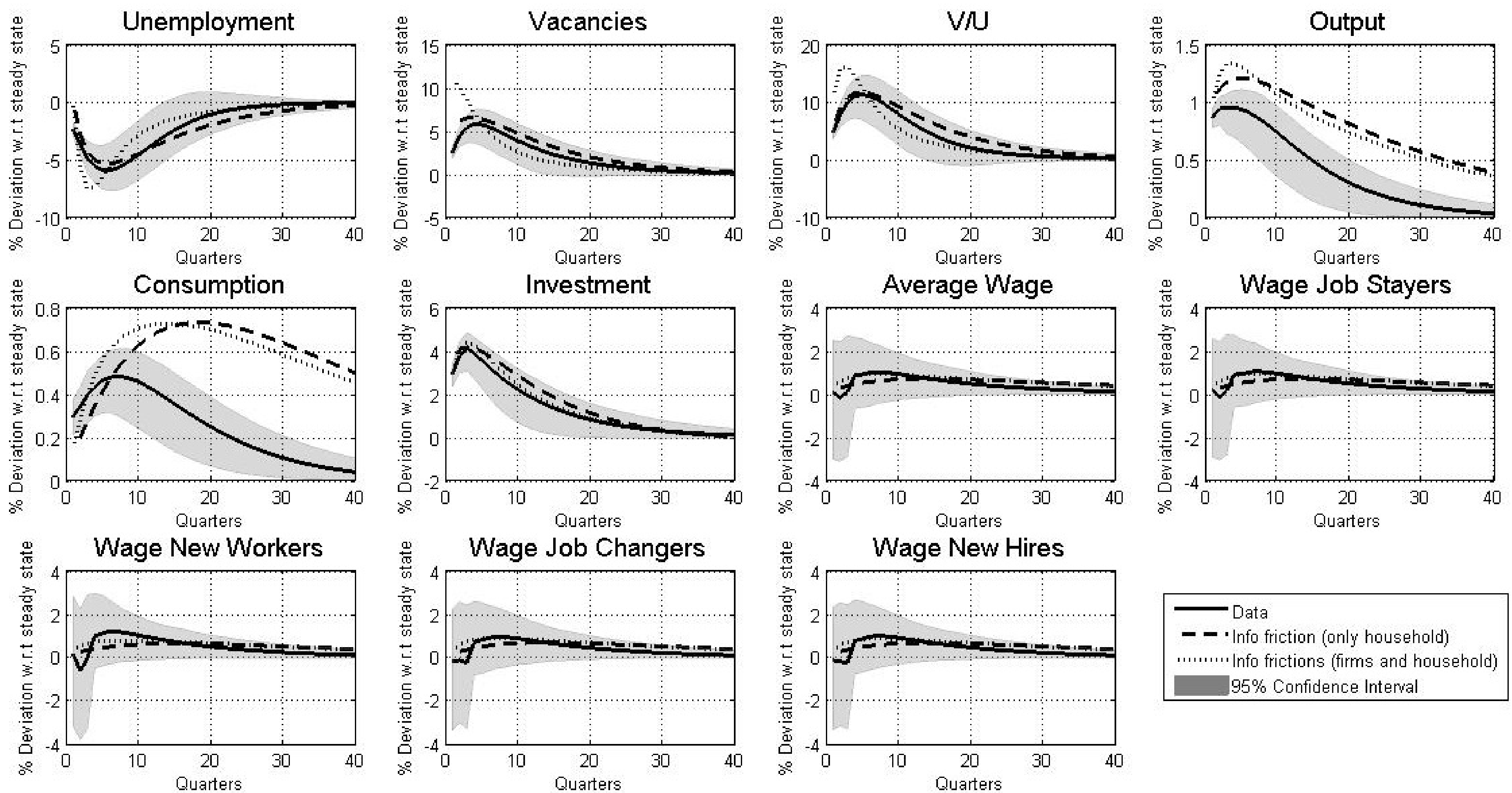
Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags (solid black lines), where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 10^5. All figures are expressed in percentage points. The x axis represents quarters after TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. Sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4. The dashed lines are the IRFs generated by a calibrated model with information frictions, in which wages for job stayers are negotiated every 4 quarters. The dotted lines are the IRFs generated by a calibrated model, in which all agents have perfect information and in which wages for job stayers are negotiated every 4 quarters.

Figure 11: IRFs to 1% Increase in Aggregate Productivity
Data versus Model with Information Frictions (firms and Workers)



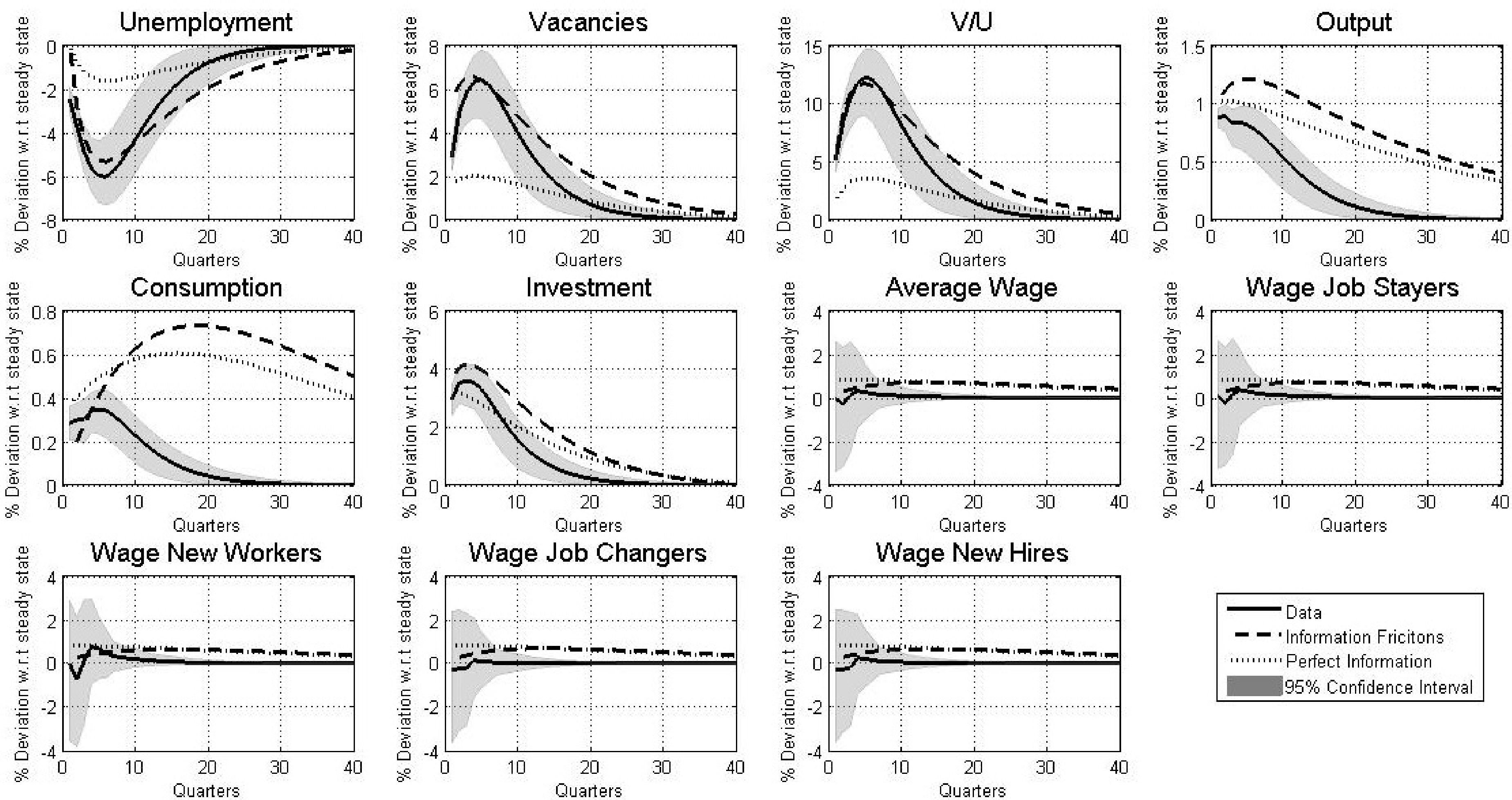
Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags (solid black lines), where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 10^5. All figures are expressed in percentage points. The x axis represents quarters after TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. Sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4. The dashed lines are the IRFs generated by a calibrated model with information frictions affecting only workers, and the dotted lines are the IRFs generated by a non-calibrated model in which all agents face information frictions (firms and workers). For details see section 5.2.

Figure 12: IRFs to 1% Increase in Aggregate Productivity
Data versus Model with Information Frictions Affecting Firms and Workers



Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags (solid black lines), where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 10^5. All figures are percentage points. The x axis represents quarters after TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. The sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4. The dashed lines are the IRFs generated by a calibrated model, in which only workers face information frictions (benchmark). The dotted lines are the IRFs generated by a re-calibrated model with information frictions in which both firms and workers face information frictions.

Figure 13: IRFs to 1% Increase in Aggregate Productivity
Data versus Model (Data filtered with smoothing parameters equal to 1,600)



Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags (solid black lines), where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs using a smoothing parameter equal to 1,600. All figures are expressed in percentage points. The x axis represents quarters after TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. The sample period is 1964Q1-2014Q4. The sample period for wages is 1994Q1-2014Q4. The dashed lines are the IRFs generated by a calibrated model with information frictions, and the dotted lines are the IRFs generated by a calibrated model in which all agents have perfect information.

Table 7: Statistics for Business Cycle Driven by TFP: U.S. Economy 1964:Q1-2014:Q4

		u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
Standard deviation		0.137	0.127	0.254	0.023	0.012	0.083	0.020	0.020	0.023	0.019	0.020	0.017
		(0.025)	(0.023)	(0.046)	(0.002)	(0.002)	(0.009)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(-)
Autocorrelation		0.972	0.967	0.969	0.953	0.975	0.950	0.962	0.961	0.936	0.949	0.949	0.904
		(0.006)	(0.008)	(0.006)	(0.006)	(0.005)	(0.008)	(0.316)	(0.323)	(0.303)	(0.315)	(0.310)	(-)
Correlation Matrix	u	1	-0.986	-0.996	-0.960	-0.920	-0.937	-0.857	-0.866	-0.850	-0.811	-0.818	-0.856
			(0.043)	(0.019)	(0.039)	(0.091)	(0.047)	(0.466)	(0.452)	(0.409)	(0.487)	(0.474)	(0.049)
	v		1	0.996	0.983	0.926	0.974	0.871	0.879	0.849	0.830	0.834	0.909
				(0.010)	(0.041)	(0.085)	(0.047)	(0.467)	(0.452)	(0.419)	(0.491)	(0.478)	(0.046)
	v/u			1	0.972	0.916	0.960	0.888	0.897	0.873	0.842	0.848	0.888
					(0.037)	(0.087)	(0.045)	(0.470)	(0.455)	(0.417)	(0.493)	(0.480)	(0.045)
	y				1	0.945	0.976	0.872	0.882	0.856	0.827	0.833	0.942
						(0.044)	(0.088)	(0.442)	(0.427)	(0.373)	(0.464)	(0.447)	(0.056)
	c					1	0.861	0.911	0.911	0.897	0.897	0.900	0.790
							(0.026)	(0.481)	(0.466)	(0.418)	(0.505)	(0.490)	(0.026)
	Inv						1	0.759	0.774	0.749	0.693	0.703	0.974
								(0.487)	(0.473)	(0.434)	(0.511)	(0.498)	(0.021)
	w^a							1	0.999	0.993	0.990	0.992	0.672
									(0.023)	(0.068)	(0.033)	(0.027)	(0.497)
	w^s								1	0.990	0.985	0.987	0.695
										(0.074)	(0.061)	(0.053)	(0.482)
	w^u									1	0.983	0.988	0.646
											(0.091)	(0.070)	(0.449)
	w^c										1	1.000	0.590
												(0.004)	(0.521)
	w^n											1	0.598
													(0.509)
	a												1

Notes: This table reports the business cycle moments driven by TFP shocks and their standard deviation (in parentheses) computed via bootstrap. For more details see Table 2.

Table 8: Simulated Business Cycle.
Calibrated Model in which Both Firms and Workers Face Information Frictions.

		u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
Standard deviation		0.125	0.165	0.273	0.025	0.013	0.082	0.018	0.018	0.016	0.018	0.017	0.018
Autocorrelation		0.900	0.803	0.912	0.935	0.986	0.937	0.975	0.975	0.974	0.974	0.974	0.871
Correlation Matrix	u	1	-0.757	-0.918	-0.850	-0.465	-0.928	-0.736	-0.736	-0.703	-0.735	-0.726	-0.824
	v		1	0.954	0.791	0.254	0.890	0.538	0.538	0.523	0.538	0.533	0.895
	v/u			1	0.870	0.368	0.966	0.664	0.664	0.640	0.664	0.657	0.921
	y				1	0.769	0.949	0.940	0.940	0.931	0.940	0.938	0.974
	c					1	0.543	0.929	0.928	0.945	0.929	0.934	0.634
	Inv						1	0.810	0.810	0.786	0.809	0.802	0.965
	w^a							1	1.000	0.998	1.000	1.000	0.847
	w^s								1	0.997	1.000	0.999	0.847
	w^u									1	0.998	0.999	0.836
	w^c										1	1.000	0.847
	w^n											1	0.844
	a												1

Notes: Statistics for the simulated economy when both firms and workers face information frictions: u: Unemployment level. v: Vacancies v/u: Vancancy-unemployment ratio. y: Output. c: Consumption. Inv: Investment. w^a: Average wage in the economy. w^s: Average wage for job stayers. w^u: Average wage for new workers (workers who were unemployed in the previous period). w^c: Average wage for job changers. w^n: Average wage for new hires (new workers + job changers). a: Aggregate TFP. All series are seasonally adjusted, logged, and detrended with the HP filter with a smoothing parameter of 100,000.

Table 9: Business Cycle Moments (Data versus Model)

	u	v	v/u	y	c	Inv	w^a	w^s	w^u	w^c	w^n	a
	Standard Deviation											
Data	0.18	0.18	0.35	0.02	0.02	0.10	0.08	0.08	0.09	0.08	0.08	0.02
Filtered Data	0.14	0.13	0.25	0.02	0.01	0.08	0.02	0.02	0.02	0.02	0.02	0.02
Model	0.11	0.16	0.26	0.02	0.01	0.09	0.01	0.01	0.01	0.01	0.01	0.02
	Auto-correlation											
Data	0.96	0.95	0.96	0.94	0.96	0.92	0.21	0.19	0.17	0.23	0.22	0.91
Filtered Data	0.97	0.97	0.97	0.95	0.98	0.95	0.96	0.96	0.94	0.95	0.95	0.90
Model	0.96	0.92	0.96	0.93	0.99	0.93	0.98	0.98	0.98	0.98	0.98	0.87
	Correlation with output											
Data	-0.88	0.90	0.94	1.00	0.89	0.82	0.17	0.17	0.18	0.15	0.15	0.80
Filtered Data	-0.96	0.98	0.97	1.00	0.95	0.98	0.87	0.88	0.86	0.83	0.83	0.94
Model	-0.88	0.90	0.94	1.00	0.70	0.93	0.85	0.85	0.82	0.85	0.84	0.95
	Correlation with TFP											
Data	-0.48	0.53	0.52	0.80	0.73	0.69	0.17	0.17	0.17	0.15	0.15	1.00
Filtered Data	-0.86	0.91	0.89	0.94	0.79	0.97	0.67	0.70	0.65	0.59	0.60	1.00
Model	-0.81	0.93	0.93	0.95	0.97	0.47	0.66	0.66	0.64	0.66	0.66	1.00

Notes: This table reports business cycle statistics for the U.S. economy and a simulated economy. Statistics reported in the Data, Filter data, and Model rows were previously presented in Tables 1, 2, and 5. *u:* Unemployment level. *v:* Vacancies *v/u:* Vancancy-unemployment ratio. *y:* Output. *c:* Consumption. *Inv:* Investment. *w^a:* Average wage in the economy. *w^s:* Average wage for job stayers. *w^u:* Average wage for new workers (workers who were unemployed in the previous period). *w^c:* Average wage for job changers. *w^n:* Average wage for new hires (new workers + job changers). *a:* Aggregate TFP.

B Proofs

B.1 Proof of Lemma 1

If all agents in the economy have complete and perfect information, the following strategy profiles constitute the unique sub-game perfect Nash equilibrium of this game:

- *For the worker:*
  - *To accept only wage offers greater than or equal to* x^* *where* $\overrightarrow{W}_j(x^*, \omega, \Omega) - U(\omega, \Omega) = \vartheta \cdot S_j$
  - *To demand a wage equal to* y^* *such that* $\overrightarrow{W}_j(y^*, \omega, \Omega) - U(\omega, \Omega) = S_j$ *and* $\overrightarrow{J}_j(y^*, \omega_f, \Omega) = 0$.
- *For the firm:*
  - *To offer* x^*.
  - *To accept only wage demands that are less than or equal to* y^*.

Proof. I begin at the third stage of the game (i.e. when the worker makes an offer). At this stage, the firm will accept any wage demand y as long as $\overrightarrow{J}_j(y, h_j, \Omega) \geq 0$. Hence, the worker will demand a wage y^* such that $\overrightarrow{J}_j(y^*, h_j, \Omega) = 0$ and she keeps all the match surplus. Thus, at the second stage (i.e. when the worker has to accept or reject the firm's offer), the worker knows that if she rejects this offer, her expected payoff at the third stage will be $\vartheta \cdot S_j$. Therefore, she will only accept wage offers that are greater than or equal to x^* where $\overrightarrow{W}_j(x^*, \omega, \Omega) - U = \vartheta \cdot S_j$. Finally, at the first stage of the game (i.e. when the firm makes an initial offer), the firm anticipates a payoff of zero if it makes an offer less than x^* and a payoff of $\overrightarrow{J}_j(x, h_j, \Omega)$ if $x \geq x^*$. Hence, the firm offers exactly x^* to the worker and she accepts it. □

B.2 Proof of Lemma 2

Suppose that agents are information-constrained as described in section 2.4. If there is an equilibrium in which firms' strategy is to reveal the aggregate state of the economy, the best strategy for firms is the same strategy described in Lemma 1.

Proof. Since we are considering the equilibrium of the game, if firms are following a revealing strategy, workers know it and behave rationally. As a consequence, workers can perfectly infer the current state of the economy based on the firm's wage offer.

Hence, a worker knows that she will receive, in expectation, $\vartheta \cdot S_j$ if she rejects a firm's offer. Therefore, the optimal strategy for workers is:

- Infer the current level of the aggregate productivity based on firm's offer x: $a = x^{-1}(a)$
- To accept only wage offers greater than or equal to x^* where:

$$\overrightarrow{W}_j(x^*, \omega, \Omega) - U = \vartheta \cdot S_j$$
$$\overrightarrow{J}_j(x^*, \omega, \Omega) = 0$$

- To demand a wage equal to y^* if she has the chance such that:

$$\overrightarrow{W}_j(y^*, \omega, \Omega) - U = S_j$$

Now, given the workers' strategy, the firm anticipates a payoff of zero if it makes an offer less than x^* and a payoff of $\overrightarrow{J}_j(x, h_j, \Omega) - U$ if $x \geq x^*$. Given that $\overrightarrow{J}_j(x, h_j, \Omega)$ is strictly decreasing in x, the optimal strategy for firms, *assuming that they follow a revealing strategy* is:

- To offer x^*.
- To accept only wage demands that are less than or equal to y^*.

As a consequence, if there exists an equilibrium in which firms reveal the true state of the economy, in equilibrium firms offer exactly x^* and workers will accept it. In other words, workers rationally believe that if a firm extents a wage offer x, it has to be the case that $x = x^*$. □

B.3 Proof of Lemma 3

If agents in the economy are information-constrained as described in section 2.4, then in equilibrium, firms do not follow a strategy in which they perfectly reveal the true state of the economy.

Proof. Suppose not. By Lemma B.2, if there is an equilibrium in which firms reveal the true state of the economy, firms always offer $x = x^*$ and workers accept all wage offers (x) because they rationally believe that x is always equal to x^*. However, in order for these strategies to be an equilibrium, firms cannot have incentives to deviate.

Suppose that firms deviate to an strategy in which they offer $\tilde{x} = 0.5x^*$. Workers will accept this offer because they believe $\tilde{x} = x^*$, and firms will be better off because $J_j(\tilde{x}) > J_j(x^*)$. Therefore, there is not an equilibrium in which firms reveal the true state of the economy. □

B.4 Proof of Lemma 4

If agents in the economy are information-constrained as described in section 2.4, the following strategy profiles constitute a sub-game perfect Nash equilibrium:

- *For the worker:*
  - *To accept only wage offers greater than or equal to x^{**} where:*

$$E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(x^{**},\omega,\Omega)-U(\omega,\Omega)\right]=\vartheta\cdot E_{\mathcal{I}_h}\left[S_j\right]$$

  - *To demand a wage equal to y^{**} such that:*

$$E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(y^{**},\omega,\Omega)-U(\omega,\Omega)\right]=E_{\mathcal{I}_h}\left[S_j\right]$$

- *For the firm:*
  - *To offer x^{**}.*
  - *To accept only wage demands that are less than or equal to $\tilde{y}^{**}$ such that $\overrightarrow{J}_j(\tilde{y}^{**},\omega_f,\Omega)=0$.*

Proof. I begin at the third stage of the game (i.e. when the worker gets to make an offer). At this stage, the firm will accept any wage demand y as long as its expected value is greater than or equal to zero. Given the firm's strategy, the firm's offer does not reveal its information. Therefore, the worker will demand a wage y^{**} such that, given her information set, firm's value is zero. Thus, at the second stage (i.e. when the worker has to accept or reject the firm's offer), the worker knows that if she rejects this offer, her expected payoff at the third stage will be $\vartheta\cdot E_{\mathcal{I}_h}\left[S_j\right]$. Therefore, she will only accept wage offers that are greater than or equal to x^{**}. Finally, at the first stage of the game (i.e. when the firm makes an offer), the firm anticipates a payoff of zero if it makes an offer less than x^{**} and a payoff of $\overrightarrow{J}_j(x,h_j,\Omega)\geq 0$ if $x\geq x^{**}$. Hence, the firm offers exactly x^{**} to the worker and she accepts it. $\square$

C Detailed Household's Problem

This appendix presents the household's problem in recursive form and the complete derivation of the employment and unemployment functions. The household's utility function is given by:

$$\mathbb{U}(\omega, \Omega) = \frac{c^{1-\sigma}}{1-\sigma} - \Psi \int_0^1 \frac{h_j^{1+\xi}}{1+\xi} dj + \beta E\left[\mathbb{U}(\omega', \Omega')\right] \tag{54}$$

Hence, the household's problem is:

$$\max_{c,k',\{h_j'\}_{j=0}^1,\{i_j'\}_{j=0}^1} E_{\mathcal{I}_h}\left\{\mathbb{U}(\omega, \Omega)\right\} \tag{55}$$

subject to the budget constraint, the law of motion of labor, and the perceived law of motion of the economy:

$$\begin{aligned} c + k' = {} & (r + 1 - \delta_k)k + \int_0^1 w_j h_j dj + \int_0^1 \pi_j dj + b \cdot u - T \\ & - \int \mu \frac{(i_j - \bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h)h_j dj \end{aligned} \tag{56}$$

$$h_j' = (1-\delta_h)(1 - q i_j F_j)h_j + q\left(\frac{v_j}{v}\right)u + \int_0^j q i_x \left(\frac{v_j}{v}\right)(1-\delta_h)h_x dx \tag{57}$$

$$u = \int_0^1 (1 - h_j) dj \tag{58}$$

$$\Omega' = \lambda^h(\Omega) \tag{59}$$

$$i_j \geq \bar{i} \qquad \forall j \tag{60}$$

where $E_{\mathcal{I}_h}[\cdot]$ is the expectation conditional on the household information set $\mathcal{I}_h$. $\omega = \{k, \{h_j\}, \mathcal{I}_h\}$ is the vector of state variables for household, and Ω is a vector that summarizes the aggregate state of the economy. Letting ϕ_c and ϕ_j denote the Lagrange multipliers for equations (56) and (57), the first order conditions are given by:

$$
\begin{aligned}
c: &\quad E_{\mathcal{I}_h}\left\{c^{-\sigma} - \phi_c\right\} && = 0 && (61)\\
k': &\quad E_{\mathcal{I}_h}\left\{-\phi_c + \beta\phi_c'(r' + 1 - \delta_k)\right\} && = 0 && (62)\\
i_j: &\quad E_{\mathcal{I}_h}\{q\int_j^1 \phi_x\left(\frac{v_x}{v}\right)(1-\delta_h)hjdx - \phi_j qF_j(1-\delta_h)h_j \\
&\qquad\qquad - \mu\left(i_j - \bar{i}\right)^{\epsilon}(1-\delta_h)h_j\} && \leq 0 && (63)\\
h_j': &\quad E_{\mathcal{I}_h}\{-\phi_j - E\{\beta\Psi {h_j'}^{\xi} + \beta\phi_c'\left(w_j' - b - (1-\delta_h)\mu\frac{\left(i_j' - \bar{i}\right)^{1+\epsilon}}{1+\epsilon}\right) \\
&\quad + (1-\delta_h)(1 - q'i_j'F_j')\beta\phi_j' - q'\int_0^1 \beta\phi_x'\left(\frac{v_x'}{v'}\right)dx \\
&\quad + (1-\delta_h)q'i_j'\int_j^1 \beta\phi_x'\left(\frac{v_x'}{v}\right)dx\}\} && = 0 && (64)
\end{aligned}
$$

Hence, combining (61) and (64) and lagging one period:

$$
\begin{aligned}
E_{\mathcal{I}_h}\{(W_j(\omega,\Omega) - U(\omega,\Omega))\} = \max_{i_j \geq \bar{i}} \quad & E_{\mathcal{I}_h}\{w_j - z_j - \mu\frac{\left(i_j - \bar{i}\right)^{1+\epsilon}}{1+\epsilon}(1-\delta_h) \\
& + E\{Q((1-\delta_h)(1 - qi_jF_j)(W_j(\omega',\Omega') - U(\omega',\Omega')) \\
& + (1-\delta_h)qi_jF_j(\tilde{W}_j(\omega',\Omega') - U(\omega',\Omega')) \\
& - q\left(\bar{W}(\omega',\Omega') - U(\omega',\Omega')\right))\}\} \qquad (65)
\end{aligned}
$$

where:

$$
(W_j(\omega',\Omega') - U(\omega',\Omega')) = \frac{\phi_j}{\beta\phi_c'} \qquad (66)
$$

Also from the first order conditions, we can verify that the optimality conditions for c and i_j are given by:

$$
\begin{aligned}
c^{-\sigma} &= \beta E_{\mathcal{I}_h}\left[(1 - \delta + r'){c'}^{-\sigma}\right] && (67)\\
i_j &= max\left\{0, \quad E_{\mathcal{I}_h}\left(\frac{qF_jQ\left(\tilde{W}_j(\omega',\Omega') - W_j(\omega',\Omega')\right)}{\mu}\right)^{\frac{1}{\epsilon}}\right\} + \bar{i} && (68)
\end{aligned}
$$

D Recursive Competitive Equilibrium (Equations)

This appendix presents the equations that characterize the recursive competitive equilibrium.

$$c^{-\sigma} = \beta E_{\mathcal{I}_h}\left[(1-\delta+r')c'^{-\sigma}\right] \tag{69}$$

$$i_j = max\left\{0, \quad E_{\mathcal{I}_h}\left(\frac{qF_jQ\left(\tilde{W}_j(\omega',\Omega') - W_j(\omega',\Omega')\right)}{\mu}\right)^{\frac{1}{\epsilon}}\right\} + \bar{i} \tag{70}$$

$$\kappa_v(v_j) = E\left[\tilde{q}_j \cdot Q \cdot J_j'(\omega_f',\Omega')\right] \tag{71}$$

$$r = \quad p_j\left(\frac{h_j}{k_j}\right)\left(\frac{\alpha}{1-\alpha}\right) \tag{72}$$

$$h_j' = (1-\delta_h)(1-i_jq_tF_j)h_j + \tilde{q}_jv_j \tag{73}$$

$$c + k' = (r+1-\delta_k)k + \int_0^1\left[w_jh_j + \pi_j - \mu\frac{(i_j-\bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h)h_j\right]dj \tag{74}$$

$$z_j = b + \Psi c^{\sigma}h_j^{\xi} \tag{75}$$

$$\pi_j = y_j - w_jh_j - rk_j - \kappa(v_j) \tag{76}$$

$$Q = \beta\left(\frac{c'}{c}\right)^{-\sigma} \tag{77}$$

$$\theta = \left(\frac{v}{s}\right) \tag{78}$$

$$y_j = e^{a_j+a}\left(k_j^{\alpha}h_j^{1-\alpha}\right)^{\gamma} \tag{79}$$

$$F_j = \int_j^1 \frac{v_x}{v}dx \tag{80}$$

$$\tilde{q}_j = \tilde{q}^u + \tilde{q}_j^c \tag{81}$$

$$\tilde{q}^u = \tilde{q}\cdot\left(\frac{u}{s}\right) \tag{82}$$

$$\tilde{q}_j^c = \tilde{q}\cdot\left(\int_0^j \frac{(1-\delta_h)i_xh_x}{s}dx\right) \tag{83}$$

$$q = m(v,s)/s \tag{84}$$

$$v = \int_0^1 v_j(\omega_f,\Omega)dj \tag{85}$$

$$y = \int_0^1 y_j(\omega_f,\Omega)dj \tag{86}$$

$$s = u + \int_0^1 i_j(\omega,\Omega)h_j(\omega_f,\Omega)dj \tag{87}$$

$$u = \int_0^1 (1-h_j(\omega_f,\Omega))dj \tag{88}$$

$$k = \int_0^1 k_j(\omega_f, \Omega) dj \tag{89}$$

$$\vartheta \cdot E_{\mathcal{I}_h}[S_j] = E_{\mathcal{I}_h}\left[\overrightarrow{W}_j(w_j, \omega, \Omega) - U(\omega, \Omega)\right] \tag{90}$$

$$\mathbb{U}(\omega, \Omega) = \frac{c^{1-\sigma}}{1-\sigma} - \Psi \int_0^1 \frac{h_j^{1+\xi}}{1+\xi} dj + \beta E\left[\mathbb{U}(\omega', \Omega')\right] \tag{91}$$

$$U(\omega, \Omega) = b + E\left\{Q\left((1-q) \cdot U(\omega', \Omega') + q \cdot \int_0^1 W_x(\omega', \Omega') \frac{v_x}{v} dx\right)\right\} \tag{92}$$

$$\begin{aligned}(W_j(\omega, \Omega) - U(\omega, \Omega)) &= w_j - z_j - \mu \frac{(i_j - \bar{i})^{1+\epsilon}}{1+\epsilon}(1-\delta_h) \\ &+ E\{Q((1-\delta_h)(1-qi_jF_j)(W_j(\omega', \Omega') - U(\omega', \Omega')) \\ &+ (1-\delta_h)qi_jF_j(\tilde{W}_j(\omega', \Omega') - U(\omega', \Omega')) \\ &- q\left(\bar{W}(\omega', \Omega') - U(\omega', \Omega')\right))\}\end{aligned} \tag{93}$$

$$\tilde{W}_j(\omega', \Omega') = \int_j^1 W_x(\omega', \Omega') \frac{v_x}{v_t} \cdot F_j^{-1} dx \tag{94}$$

$$\bar{W}(\omega', \Omega') = \int_0^1 W_x(\omega', \Omega') \frac{v_x}{v} dx \tag{95}$$

$$\Pi_j(\omega_f, \Omega) = \pi_j + E\left[Q\Pi_j(\omega_f', , \Omega')\right] \tag{96}$$

$$J_j(\omega_f, \Omega) = p_j - w_j + E\left[Q \cdot (1-\delta_h)(1-i_jqF_j) \cdot J_j(\omega_f', \Omega')\right] \tag{97}$$

$$S_j = J_j(\omega_f, \Omega) + W_j(\omega, \Omega) - U(\omega, \Omega) \tag{98}$$

$$\hat{a} = a + n \tag{99}$$

$$a' = \rho_a \cdot a + e_a' \tag{100}$$

$$n' = \rho_n \cdot n + e_n' \tag{101}$$

E Wages

In this appendix, I present more details about my empirical exercise and some additional experiments using other wage series.

E.1 Wage series

I use the Current Population Survey (CPS) to construct wage series adjusted for composition effects. The CPS is the main labor force survey for the U.S., and it is the primary source of labor force statistics such as the national unemployment rate. The CPS consists of a rotating panel where households and their members are surveyed for four consecutive months, not surveyed for the following eight months, and interviewed again for another four consecutive months. The CPS includes individual information such as employment status, sex, education, race, state, etc. However, individual earnings and hours worked are collected only in the fourth and eight interviews. In addition, since 1994, individuals have been asked if they still work in the same job reported in the previous month, making it possible to identify job changers. Following Muller (2012) and Haefke, Sonntag and van Rens (2013), my empirical model is based on the following equation:

$$log(w_{it}) = X_{it}\beta + log(\tilde{w}_{it}) \tag{102}$$

where w_{it} is the hourly wage rate for individual i at time t, X_{it} is a vector of individual characteristics, and $\tilde{w}_{it}$ is the component of the wage rate for individual i at time t that is orthogonal to individual i's characteristics. The hourly wage rate is constructed by dividing weekly earnings by weekly hours. Following Schmitt (2003), top-coded weekly earnings are imputed assuming a log-normal cross-sectional distribution for earnings. Following Haefke et al. (2013) I drop hourly wage rates below the 0.25th and above the 99.75th percentiles each month. In order to take into account changes over time in the regression coefficients, I estimate equation (102) period by period controlling for: education, a fourth order polynomial in experience, gender, race, marital status, state, 10 occupation dummies, and 14 industry dummies.[48] Then, I use the residuals from this Mincer regression to construct the average wage for each group as:

$$log\left(w_t^G\right) = \sum_{i \in G} log\left(\tilde{w}_{it}\right)\omega_{it} \tag{103}$$

where G={All, Job stayers, New hires, Job Changers, New hires from unemployment (new workers)}, and ω_{it} is individual i's weight.[49] Due to sample design, it is not possible to match

[48]For occupation and industry, I use variables OCC1950 and IND1950 provided by IPUMS-CPS. Experience is defined as age minus years of education minus 6.

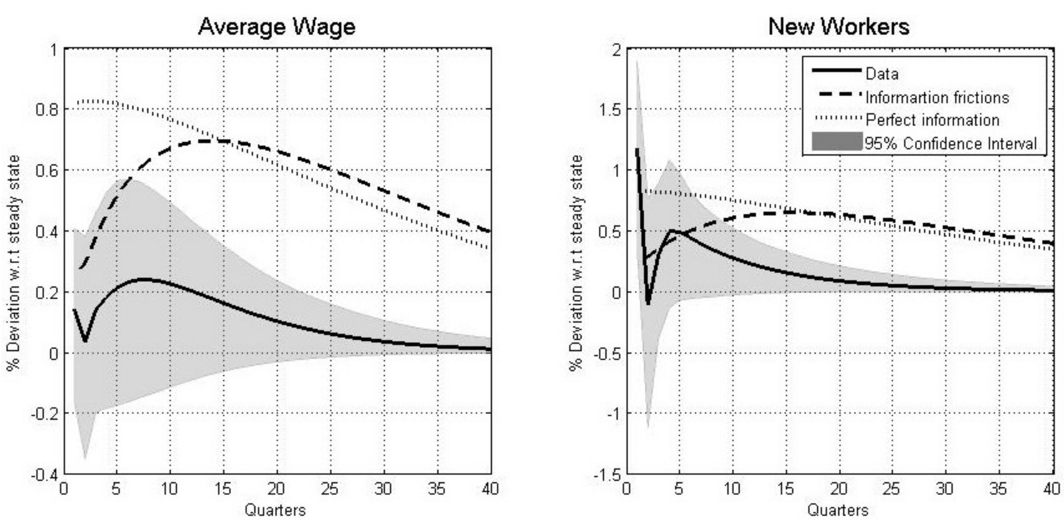
[49]Following the literature, individual i's weight is the product of the individual weight reported by the BLS and

individuals in the fourth quarter of 1995. Hence, with the exception of the average wage for all workers, wage series have a missing value in this period. In order to fill these missing observations, for continuity, I impute these series using the average wage for all workers. However, my results are robust to limiting my sample period to 1996-2014.

E.2 Alternative wage series (Haefke et al, 2013)

Haefke et al. (2013) constructed two wage series for production and non-supervisory employees adjusted for composition effects, which they have kindly made available online. In this subsection, I show that these series tell a similar story: wage responses to TFP shocks are delayed and weak. In particular, Figure 14 plots the impulse response functions of these wages to a 1% increase in aggregate TFP. The sample period is 1984Q1-2006Q1, which is the same one used in Haefke et al. (2013). In order to fill in the missing values in 1985 and 1995, I impute these series using the real aggregate wage.

Figure 14: IRFs to 1% Increase in Aggregate Productivity
Average Wage for Production and Nonsupervisory Employees



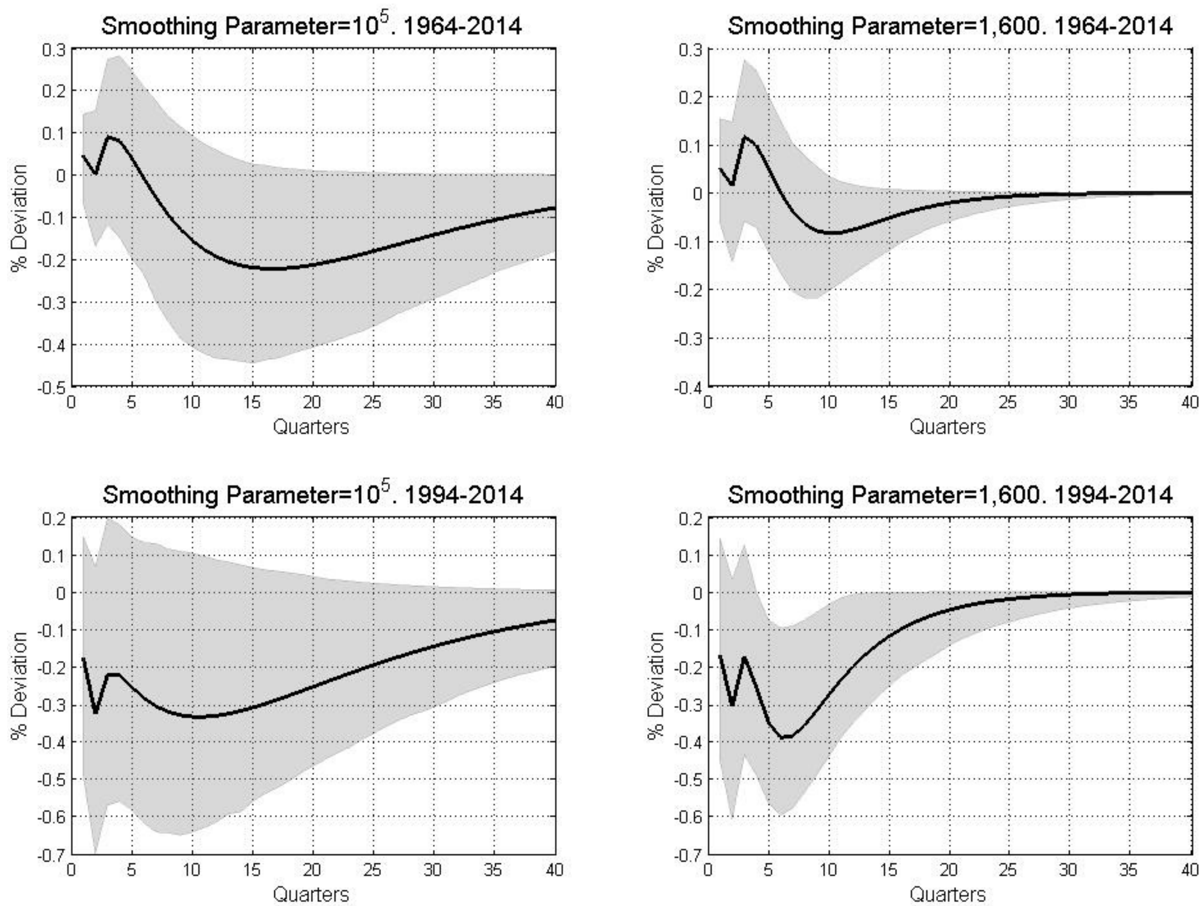
Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with two lags (solid black lines), where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs with smoothing parameter equal to 10^5. All figures are expressed in percentage points. The x axis represents quarters after the TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap. The sample period is 1984Q1-2006Q1. The dashed lines are the IRFs generated by a calibrated model, in which only workers face information frictions (benchmark). The dotted lines are the IRFs generated by a calibrated model in which all agents have perfect information.

hours worked.

E.3 Results for average wage of production and non-supervisory employees

In order to illustrate the role of composition effects, Figure 15 plots the IRFs to a 1% increase in TFP of the average wage for production and non-supervisory employees. This figure shows that this series is acyclical. Even ignoring the wide confidence intervals, the point estimates of these IRFs are very small in absolute terms.

Figure 15: IRFs to 1% Increase in Aggregate Productivity
Average Wage for Production and Nonsupervisory Employees



Note: This figure plots the impulse responses to a 1% increase in TFP from bivariate near-VARs with three lags, where TFP is taken to follow an exogenous AR(1) process. All variables are HP-filtered in logs. For the two figures at the left a smoothing parameter equal to 10^5 was used. For the tow figures at the right a smoothing parameter equal to 1,600 was used. The sample period for the top row is 1964Q1-2014Q4. The sample period the bottom row is 1994Q1-2014Q4. All figures are expressed in percentage points. The x axis represents quarters after the TFP shock. The shaded area represents the 95% confidence intervals computed via bootstrap.