Imperfect Information and Slow Recoveries in the Labor Market

Anushka Mitra *

Click here for the latest draft

This draft: January 21, 2024

Abstract

The unemployment rate remains persistently high after recessions even after job losses subside. Standard search and matching models have difficulty capturing this pattern. In this paper, I argue that noise shocks, which capture agents' expectational errors due to the noise in received signals about the persistence of aggregate productivity, can generate substantial persistence in the unemployment rate. I first identify these noise shocks using a novel structural VAR and find that unemployment would have recovered to its pre-recession level 7 quarters earlier in the absence of noise shocks in the 1968-2019 period. I then set-up a general equilibrium search and matching model with on-the-job search, endogenous search effort and wage rigidity and consider three shocks: a permanent productivity shock; a transitory productivity shock and a noise shock. The model calibrated to target standard moments and disciplined to match impulse responses identified through SVAR predicts 6 quarters longer recoveries in unemployment compared to a model without imperfect information and noise shocks. It also predicts 23 percent more volatility in unemployment and vacancies. These results are generated mainly through two channels. First, responses to persistent productivity shocks are more persistent as it takes time for agents to learn whether a shock is persistent or not. Second, noise shocks provide an additional source of persistence, which are amplified through on-the-job search and firms' vacancy posting decisions.

Keywords: Imperfect Information, Labor Market, Business Cycles
JEL Codes: E24, E32, E70

*The University of Texas at Austin, anushka@utexas.edu. I am deeply grateful to Ayşegül Şahin, Andreas Mueller and Olivier Coibion, for their constant guidance and support. I remain indebted to Saroj Bhattarai, Andres Drenik and Stefano Eusepi for their insightful discussions. I thank Gadi Barlevy, Jason Faberman, Bart Hobijn, Gizem Kosar, Giorgio Topa and Marcelo Veracierto for their feedback and insights. I further thank Sadhika Bagga, Robert Barsky, Chris Boehm, Joel David, Keshav Dogra, Filippo Ferroni, Francois Gourio, Niklas Kroner, Donggyu Lee, Thomas Lubik, Davide Melcangi, Leonardo Melosi, Nitya Pandalai-Nayar, Jane Ryngaert, Pierre Sarte, Andrea Tambalotti, Suryansh Upamanyu, Alessandro Villa, Dongchen Zhao and conference and seminar participants at UT Austin, Chicago Fed and New York Fed for helpful comments and suggestions. All errors are my own.

1 Introduction

One of the well-established stylized facts in macroeconomics is the persistence in labor market dynamics, especially the sluggish recovery of unemployment following recessionary job losses. While job losses at the onset of recessions tend to normalize quickly, the unemployment rate remains elevated much longer than the duration of the recession. Figure 1 shows that it took the unemployment rate between 5 to 16 quarters to recover half of its recessionary increase and longer than 20 quarters to recover back to its pre-recession level. The duration for recovery has become even longer over time with the Great recession being the slowest. This stylized fact continues to present a challenge for conventional business cycle models (Cole and Rogerson (1999) and more recently Hall and Kudlyak (2022)).[1]

I argue that imperfect information about the fundamental drivers of business cycles provides a natural explanation for sluggish recovery in the labor market even if the underlying shocks are not persistent. For example, professional forecasters after the Great Recession systematically over-estimated how high unemployment would be in the medium-run (see Figure 2). I proceed in two steps to establish the link between imperfect information and labor market dynamics. First, I identify noise shocks-errors in expectations due to the noise in received signals-using a structural VAR framework estimated with data on the utilization-adjusted TFP, real GDP growth and nowcast errors for the period 1968-2019. I find that unemployment would have recovered to its pre-recession level 7 quarters earlier on average, in the absence of noise shocks. Second, I introduce noise shocks into a general equilibrium search model. The model extends the textbook model along three important dimensions: on-the-job search; endogenous search effort and rigid wages. I find that noise shocks together with these features provide an intuitive explanation for the sluggish recovery of the labor market. Due to imperfect information, firms and workers observe noisy signals and cannot discern if the productivity shock is persistent or transitory. This affects forward looking decisions such as firms' hiring decisions and workers' job search decisions. Since firms and workers learn the true persistence of shocks only slowly, they respond sluggishly to changes in the economy which creates persistence in labor market dynamics.

I identify noise shocks using a using a tri-variate SVAR with utilization-adjusted TFP, real output growth and nowcast errors from the Survey of Professional Forecasters. The shocks are identified with a combination of sign restrictions and max share identification, which maximizes the forecast error variance of a target variable (Francis et al., 2014) at a chosen horizon. I consider three shocks: persistent and transitory productivity shocks and noise shocks. Noise shocks are assumed to only affect expectations about productivity but not to influence their actual levels. Therefore, noise shocks affect expected output growth more than actual output growth (Enders et al. (2021)), which still may respond due to behavioral reasons. This assumption, along with the fact that the nowcast errors, that are defined as the difference in expected output growth from the realized output growth for the same quarter, are not available to the agents contemporaneously,

[1] The peculiar labor market dynamics in the wake of COVID pandemic presented a counter example which I address in Section 6.2.3.

allows me to impose sign restrictions to identify the noise shocks. I then use the max-share method to disentangle the productivity shock into persistent and transitory components. I identify the shock that maximizes the forecast error variance of productivity in the long run as the persistent shock to productivity. I quantify the role of noise shocks in accounting for movements in the unemployment rate by computing the predicted unemployment rate due to only persistent and transitory shocks while shutting down the noise shock from the estimated SVAR. While it took on average 17 quarters for unemployment rate to recover 50% of its recessionary rise since the beginning of the recession, it would have been 11 quarters in the absence of noise shocks. Noise shocks also dampened job-finding rates and vacancies.

I analyze the impulse responses for key labor market outcomes to the noise shock about the true persistence of productivity using smooth local projections (Barnichon and Brownlees, 2019). I find that noise shocks have persistent effects on the dynamics of the labor market. Specifically, a one standard deviation noise shock leads to an increase in the unemployment rate of 0.4 percentage points at 4 quarters and recovers between 8-10 quarters. This response results from an increase in the inflow into unemployment and a decrease in the job-finding rate, influenced by a decrease in vacancies and hiring rates by firms. Wages respond weakly and are slow to adjust. These findings suggest that firms and workers overestimate the persistence of the true shock during these downturns and respond as if the recession was deeper and longer than it was. Firms reduce hiring and workers face lower job openings which keeps the unemployment rate persistently high.

There are two key takeaways from these impulse responses. First, the quantitatively and statistically significant response to a noise shock suggests the presence of information frictions. If firms and workers had perfect information about the shock being noise, noise shocks would not exist and, it would not be optimal for agents to respond to it. However, initially agents misperceive the noise shock as an actual negative productivity shock and hence firms decrease their hiring. As a result, there are fewer job opportunities for workers and job-finding rate decreases. This contributes to an increase in unemployment.

Second, the hump-shape of the impulse responses suggest that firms and workers are learning under imperfect information. Although firms and workers initially misperceive this shock as a change in fundamentals, they gradually place more weight on the shock being a noise shock. As a result, layoffs decline, hiring increases albeit slowly and the job-finding rate recovers. This ultimately results in a decline in unemployment.

Motivated by the empirical evidence, I set up a general equilibrium model of random search and matching with imperfect information. The model has several key features such as on-the-job search, endogenous search effort and wage rigidity. These choices are motivated by Cole and Rogerson (1999) who argued for incorporating heterogeneity in worker search intensity and allowing for on-the-job search as potential solutions to the slow recovery of unemployment. Specifically, both unemployed and employed workers search and their search effort is endogenous. There is a stylized job ladder with two kinds of jobs: good and bad jobs, which are idiosyncratic and revealed to the firms and workers upon matching. Good jobs offer higher wages and they hire both unemployed and employed workers. Bad jobs pay lower wages and only hire the unemployed. Employed workers in bad jobs search to move up the ladder and unemployed workers search to move to employment. Firms optimize hiring decision each period while incurring a cost of hiring. Wages are determined by staggered Nash bargaining a la Gertler and Trigari (2009) as they are only renegotiated with an exogenous probability. Therefore, on average wages exhibit sticky wages.

There are two fundamental shocks: transitory and persistent productivity shocks. Moreover, there is imperfect information about the true nature of these shocks that I introduce to capture the noise shocks: workers and firms observe aggregate productivity but cannot distinguish between its transitory and persistent components. Instead, they receive a potentially persistent noisy signal about the persistent component and use it to form beliefs about the future path of productivity. The noise introduces complexity in determining whether a shock is a true persistent productivity shock or noise in the signal. The model is calibrated by targeting key unconditional moments in the data and disciplined to match the empirical impulse responses of key labor market variables to the shocks identified from the SVAR. The model generates impulse responses consistent with the data, capturing both the magnitude as well as the hump-shape of the dynamic responses of key labor market outcomes such as unemployment, job-finding rate, job-to-job transition and vacancies.

I find that incorporating imperfect information about the underlying persistence of aggregate productivity shocks increases the persistence of unemployment relative to a full-information model where firms and workers can perfectly observe the persistent and transitory components of aggregate productivity each period, through two channels. First, the response to a persistent productivity shock in the model suggests that the effects of persistent productivity shocks are even more persistent because the agents learn about the true persistence of the shock slowly.

Agents initially attribute the shock to being persistent, transitory or noise with some probability, and under-react to the persistent shock compared to the full information framework. Consider a negative persistent productivity shock. Wages do not decrease initially. From the firms' perspective, if they adjust wages downward substantially and the shock reverses rapidly, their future discounted revenue will be lower. Unemployed and employed workers do not decrease their search effort as much, since they attribute the shock to be noise with some probability. However, as firms and workers update their beliefs about the change in productivity, they assign more weight each period to the change in productivity being truly persistent. This adjustment in expectations is significantly slowed down by the persistence in the noise as agents now face a more complex signal extraction problem. Firms that get a chance to renegotiate now offer lower wages as they assign higher weight to the shock being a true productivity shock and as a result the average wage decreases. Unemployed workers decrease their search effort as returns from employment declines. Further, employed workers looking to move up the ladder decrease their search effort as average wages have declined, it leads to firms posting fewer vacancies and dampens job-finding rates for the unemployed workers. This generates persistence in the job-finding rate, eventually leading to for a more persistent response in unemployment than the full information framework.

The second channel is that the introduction of imperfect information gives rise to the noise shocks, which provide an independent source of persistence in the labor market. When there is a negative noise shock, agents partially attribute the perceived decline in productivity to an actual change in productivity, although the true productivity remains unchanged. This leads firms to expect lower returns from new hires which subsequently reduces labor demand and the number of job vacancies. At the same time, unemployed workers who anticipate lower wages due to the perceived fall in the persistent component of productivity, decrease their search intensity, resulting in a lower job-finding rate. Employed workers also reduce their search effort as their incentive to move up the job ladder declines as they expect lower wages. In equilibrium, these factors lead to fewer matches between firms and workers, thereby increasing the unemployment rate.

During downturns, both these channels may act together to amplify the persistence of unemployment as firms and workers receive a sequence of all the shocks. Agents overestimate the persistence of the negative productivity shock due to presence of noise shocks and perceive the negative productivity shock to be persistently worse than it actually is. Since they gradually learn whether a shock is persistent or transitory, they respond as if facing a more persistent negative productivity shock than the true shock. Specifically, firms anticipate productivity to be persistently worse and therefore expect lower future revenue and post fewer vacancies for longer than would be consistent with the true decline in productivity. The decline in vacancies lower job offer arrival rates for both the unemployed and the employed who lower their search effort due to the decline in return to search. Since most of the bad jobs remain occupied by the employed workers and good jobs are hard to find, the job-finding rate of the unemployed declines further due to the congestion in the lower ranks of the ladder. Consequently, the job-finding rate declines further which keeps the unemployment rate elevated longer than implied by the true state of the economy.

I quantify the additional persistence generated by imperfect information using my model by simulating the path of unemployment for recessions between 1968-2019. I find that my baseline model with imperfect information, sticky wages and on-the-job search implies a substantially higher persistence in the unemployment rate. Specifically, it takes 15 quarters for the unemployment rate to recover 50% of its recessionary increase in the model while the corresponding number is 17 quarters in the data. In the model without imperfect information, it would take only 9 quarters. In addition, the introduction of imperfect information improves the performance of the model in explaining labor market volatility. The imperfect information model generates about 23 percent higher volatility in the unemployment rate as compared to the full information model. It also generates higher volatility in vacancies and job-finding and job-to-job transitions rates, and a relatively lower volatility of wages, consistent with the data.

This paper contributes to two strands literature. The first is on the macroeconomic effects of incomplete information on labor market dynamics and business cycles. In this regard, this paper the work on the role of beliefs as drivers of business cycles (Beaudry and Portier, 2004; Collard et al., 2009; Blanchard et al., 2013; Forni et al., 2017; Chahrour and Jurado, 2018; Lagerborg et al., 2020; Ilut and Saijo, 2021) by identifying noise shocks that are an important source of aggregate fluctuations in the labor market. Specifically, this paper contributes to the literature focusing on the role of beliefs in labor market dynamics (Den Haan and Kaltenbrunner, 2009; Theodoridis and Zanetti, 2016; Schaal, 2017; Chahrour et al., 2020; D'Agostino et al., 2022). Particularly, this paper is closely related to Faccini and Melosi (2022) who also find that noise shocks play a significant role in the labor market dynamics. This paper also complements the findings in Morales-Jiménez (2022) by providing novel empirical evidence; where imperfect information is introduced in a search and matching model and quantitative analysis finds that such a model is able to generate the volatility as well as elasticity of wages with respect to productivity consistent with the data.

Second, this paper contributes to the literature studying the labor market dynamics and in particular the persistent recovery of unemployment after recessions. It has been a feature of the postwar recoveries in the labor market that unemployment levels remains elevated, even after the initial spike in job destruction has subsided. While there is consensus in the literature about these stylized facts and changes in unemployment dynamics, a unified consensus on the driver of slow recoveries remains elusive. Some of the primary explanations that have been proposed for slow recoveries are job polarization (Jaimovich and Siu, 2020), restructuring (Koenders et al., 2005; Berger et al., 2012), changing persistence of business cycles (Bachmann, 2012; Panovska, 2017) and increasing importance of technology shocks since mid-1980s (Barnichon, 2010b). Recent papers attribute the slow recoveries to UI extensions (Mitman and Rabinovich, 2019), convergence of female employment (Fukui et al., 2023) and congestion in hiring (Mercan et al., Forthcoming, 2023). I document that noise shocks arising from imperfect information can substantially delay the recovery of the labor market, both empirically as well as quantitatively, thus contributing to this literature that has explored various aspects of labor market recovery patterns.

The rest of the paper is organized as follows. Section 2 discusses the empirical evidence and Section 3 discusses the identification of noise shocks using a structural VAR and its impact on labor market dynamics. Section 4 introduces an imperfect information structure to a general equilibrium search and matching model. Section 5 discusses the calibration and estimation strategy for the model parameters. Section 6 presents the results from the quantitative exercise and Section 7 concludes.

2 Unemployment Recoveries and Professional Forecasts

In this section, I first document the sluggish recovery of unemployment in the US data in 1968-2019. I show that it takes on average 25 quarters for the unemployment rate to recover to its pre-recession trough. I then document misperception about the unemployment rate by professional forecasters across recessions and show that forecasters consistently predict more sluggish recoveries in the labor market than what actually occurs.

Unemployment Dynamics During Recoveries. U.S. labor market recoveries typically have been slow, with the unemployment rate remaining elevated even after the job destruction subsides. To have a consistent metric of labor market recovery over time, I follow Heise et al. (2022) who propose a simple measure of labor market recovery—*the unemployment recovery gap*. I consider the share of the rise in the unemployment rate during the preceding recession that has been reversed during the subsequent expansion. Specifically, for each recession, I identify the peak quarterly unemployment rate, u_{peak} and compute the increase in the unemployment rate relative to its preceding trough, u_{trough}. This allows me to evaluate the progress in the unemployment rate $u_{peak} - u_t$ as a fraction of the unemployment gap $u_{peak} - u_{trough}$ by considering the time for 25%, 50%, 75% and 100% of the gap to recover. Specifically,

$$URecovery_t = \frac{u_{peak} - u_t}{u_{peak} - u_{trough}}. \tag{1}$$

Table 1 and Figure 1 show the unemployment recovery dynamics for each recession starting in 1968. As Table 1 shows it took the unemployment rate between 5 to 16 quarters to recover half of its recessionary increase and longer than 20 quarters to recover back to its pre-recession level. Moreover, unemployment recoveries became slower over time. On average, post-recession unemployment takes 10 quarters to reduce by 50% and 25 quarters for full recovery. Before 2000, 50% recovery occurred within 9 quarters; post-2000, this extends to 13 quarters.

Figure 1: Unemployment Recovery Across Recessions

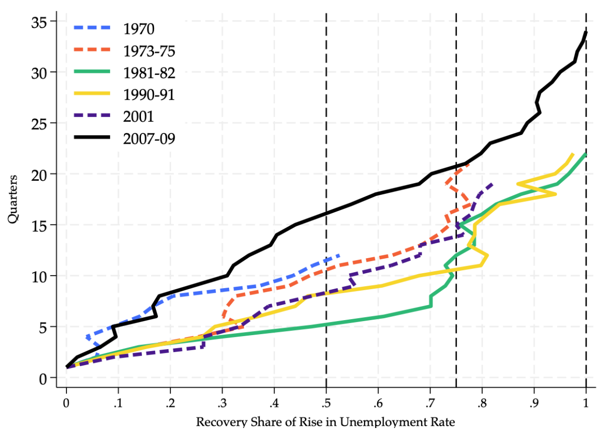


Table 1: Unemployment Recovery Across Recessions

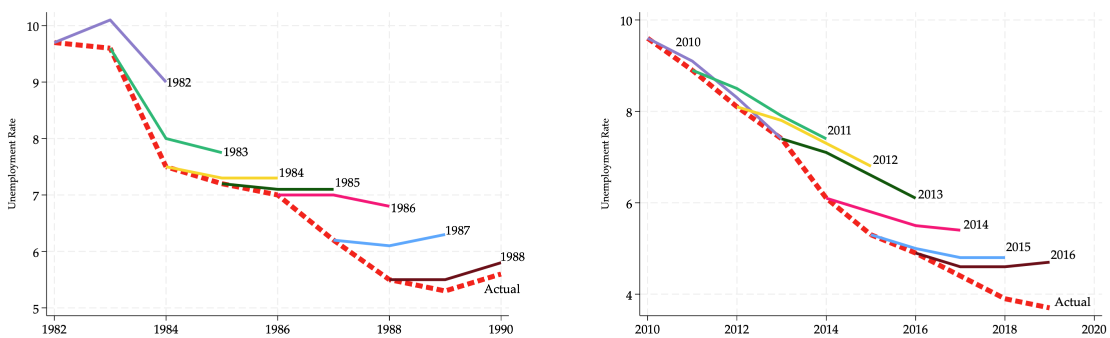
Recessions	(1) 25%	(2) 50%	(3) 75%	(4) 100%	(5) NBER
2007-09	9	16	21	33	25
2001	3	9	14	NA	40
1990-91	4	8	13	21	31
1981-82	4	5	15	22	4
1973-75	4	10	17	NA	12
1969-70	8	12	NA	NA	36
Average:					
Total	5	10	16	25	30
Pre 2000	5	9	15	22	21
Post 2000	6	13	18	33	33

Note: Figure (1) and Table (1) report the number of quarters taken to recover 25%, 50%, 70% and 100% of the rise in the unemployment rate from its peak across recessions between 1968-2019, except the recession in 1980 which was quickly followed by the downturn in 1981-82. The NBER Cycle is the duration for economic activity to go from trough to its peak during each recession.

Forecast Errors and Misperception about the Evolution of the Unemployment Rate. While the unemployment rate remains persistently elevated during recoveries, forecasters tend to be even more pessimistic about the recovery of the labor market. This is evident in the forecast errors from the Survey of Professional Forecasters. The Survey of Professional Forecasters (SPF) is a quarterly survey which elicits the expectations of professional forecasters about the state of the economy in the US. It is often regarded as a benchmark measure of private sector expectations.

The pattern is clear in long-run projections of the one, two and three year ahead unemployment rate. Figure 2a shows that forecasters consistently overestimated the unemployment rate during 1981-82 in the Livingston Survey.[2] Most recently, Figure 2b documents that professional forecasters predicted an even slower recovery after the Great recession. Figure A4 plots the median 1 year ahead unemployment rate projections from the SPF, which show that forecasters predict the recoveries to be slower than they actually were. These observations suggest that there is typically a wedge between the expected and the actual unemployment rate across recessions.

Figure 2: Unemployment Rate: Projections and Actual



(a) 1981-82 Recession

(b) 2009-07 Recession

Note: In Panel (a), the various colored lines represent the median 1 and 2 year ahead projection of the unemployment rate from the Livingston Survey. The solid red line is the actual unemployment rate during the 1981-82 recession. In Panel (b) the various colored lines represent the median long-run (1 year, 2 year and 3 year ahead) projections of the unemployment rate from the Survey of Professional Forecasters during the Great Recession. The dashed red line is the actual unemployment rate.

Taking stock. One potential explanation for the mismatch between realized and expected unemployment rates could be the imperfect information about whether the changes in the aggregate fundamental process in the economy is persistent or transitory (Edge et al., 2007). Due to imperfect information, agents must base their decisions on their expectations about the persistence of changes in the true fundamental process by observing some signals. Under such a framework, agents then may predict consistently higher unemployment rate as they cannot distinguish the true shocks in the economy from noise shocks (errors in expectations due to the noise in received signals) and these beliefs may in turn affect economic outcomes. To test this hypothesis, I proceed in two steps. I first identify noise shocks using a SVAR that I discuss in the following section. Then, I study whether aggregate labor market outcomes respond to the identified shocks.

A recent approach to identifying noise shocks relies on a measure of misperceptions: the deviation of realized outcomes from expected outcomes (Enders et al., 2021). I use the 'nowcast errors'—the difference between the actual outcome and the real-time perceived outcome—for identifying noise shocks. The nowcast errors contain significant information about the real-time

[2]The Survey of Professional Forecasters started reporting the long-run projections only since 2009. Therefore, I rely on the Livingston Survey for longer-run unemployment expectations during earlier recessions.

deviation in expectations of professional forecasters relative to realized outcomes. Since these deviations may arise due to the noise in observed signals about current economic activity, nowcast errors can be exploited to identify these noise shocks.

Nowcast Errors The nowcasts, which are median expectations about the current GDP growth rate, are collected from the Survey of Professional Forecasters. The nowcast errors are computed as the difference between the ex-post growth rate of GDP for a quarter and the contemporaneous forecast of what that growth rate would be from professional forecasters. For the rest of the paper, it is defined as

$$nce_t = \Delta y_t - \mathbf{E_t}^{median}(\Delta y_t) \tag{2}$$

where y_t is the current real GDP growth rate. The timing of the survey is such that the participating professional forecasters are asked to report their expectations about the current quarter output growth by the second month of the quarter. At this point, the current output is not observable. Therefore, at time t, nowcast errors are not observable in real time and are not part of any agent's information set. This gives an informational advantage to the econometrician over economic agents as the nowcast errors only become available ex-post. Further, these nowcast errors plays a key role in the identification of noise shocks if one assumes that nowcast errors and output growth have opposite response to noise shocks.

3 Identification of Noise Shocks

In this section, I describe the empirical strategy to identify a persistent TFP shock, a transitory TFP shock, and a noise shock and then discuss the effects of these shocks on key labor market outcomes. Here, I test the hypothesis that the observed wedge between realized and expected unemployment rates, as shown in Figure 2 and A4, arise due to imperfect information about whether the changes in the aggregate fundamental process in the economy are persistent or transitory. I proceed in two steps. First, I identify noise and productivity shocks using a tri-variate SVAR. The identification of noise shocks is achieved by imposing sign and zero restrictions. identify persistent and transitory productivity shocks by maximizing the forecast error variance of aggregate productivity in the long run. Second, using local projections, I test whether noise shocks have a significant effects on the dynamics of key labor market indicators like unemployment and vacancies.

Empirical Specification. The aggregate productivity process is assumed to consist of a persistent and a transitory component. While the level of productivity is observable, its underlying components are not. Therefore, economic agents must form their beliefs about aggregate productivity using public signals. Noise shocks are the changes in the signal not coming from shocks to the actual productivity. The aim is to now identify the three shocks, a persistent shock to aggregate productivity, a transitory shock to aggregate productivity and a noise shock. The empirical specification consists of a vector-autoregression of the form

$$A_0\mathbf{Y}_t = a + \Sigma_{j=1}^{p} A_j\mathbf{Y}_{t-j} + e_t \tag{3}$$

where the set of variables $\mathbf{Y}_t \equiv [TFP_t, GDP_t, NCE_t]$ includes the utilization-adjusted TFP from Fernald (2014), real GDP growth and Nowcast errors.[3] The sample period ranges from 1968q4 to 2019q4. A_j is the weight on past realizations of Y_t, e_t is a vector of structural economic shocks, and A_0^{-1} is the structural matrix that the SVAR procedure seeks to identify from the set of reduced-form residuals. The fact that agents cannot observe the nowcast errors in real time provides the econometrician an informational advantage over the economic participants in real time, thus making the SVAR model invertible (Blanchard et al., 2013).

It follows that the reduced-form representation is

$$y_t = b + \Sigma_{j=1}^{p} B_j y_{t-j} + u_t \tag{4}$$

Here $b = A_0^{-1}$ is an $n \times 1$ vector of constants, $B_j = A_0^{-1}A_j$, $u_t = A_0^{-1}\epsilon_t$. $var(\mathbf{u}_t) = E(\mathbf{u}_t\mathbf{u}_t') = \sum = \mathbf{A_0^{-1}}(\mathbf{A_0^{-1}})'$ is the $n \times n$ variance-covariance matrix of reduced-form errors. Let $\boldsymbol{\phi} = (\mathbf{B}, \sum)$ collect the reduced-form parameters. Finally, following Uhlig (2005) , I define the set of all IRFs through an $n \times n$ orthonormal matrix $\mathbf{Q} \in \Theta(n)$ where $\Theta(n)$ is the set of all $n \times n$ orthonormal matrices.

Identification Assumptions Aggregate noise shocks in an imperfect information structure are identified in the data using a combination of zero and sign restrictions as well as max share identification in a tri-variate structural VAR. The sign restrictions identify the noise shock and the max-share approach identifies the persistent shocks from the transitory productivity shocks.

1. I impose the following restrictions on the impact matrix to identify the noise shocks.

   (a) Noise shocks have zero impact on aggregate productivity. Noise is an error in the expectations of economic agents. It should not affect the underlying fundamental productivity process in the economy, which is the total factor productivity here. I use the TFP series from Fernald (2014) and assume that this is an error-free measure of TFP.

   (b) On impact, the persistent and the transitory TFP shocks contemporaneously affect TFP and GDP growth in the same direction. The response of the nowcast error to a persistent as well as a transitory shock is unrestricted.[4]

   (c) Noise shocks contemporaneously affect nowcast errors in the opposite direction as they do GDP growth. In other words, noise shocks are assumed to move expectations about

[3] The fact that the VAR does not include any labor market outcomes such as the unemployment rate, allows the identified shocks to be unaffected by fluctuations in the labor market directly.

[4] A TFP shock *may* cause a larger change in actual GDP growth than it does in expectations as evidence suggests that consensus forecasts under-react relative to full-information rational expectations (Bordalo et al., 2020). For robustness, I consider an alternate specification where I impose the restriction that the TFP shocks affect the nowcast error in the same direction as TFP and output. However, the results from this exercise are in line with the main exercise.

real GDP more than real GDP itself. GDP also increases as agents respond but it increases less than the expectations. This implies that $nce_t = \Delta y_t - \mathbf{E_t}^{median}(\Delta y_t) < 0$ while $\Delta y_t > 0$. This assumption is made by Enders et al. (2021) and Chahrour et al. (2021) who identify belief shocks in a bi-variate VAR using sign restrictions.

These identifying restrictions hold across a broad class of models with information structures consistent with Lorenzoni (2009), Blanchard et al. (2013), and Angeletos and La'o (2010). Let ϵ_t be the persistent shock, η_t be the transitory shock and ν_t be the noise shock. Thus, the restrictions on the impact matrix can be demonstrated by the following:

$$\begin{bmatrix} z_t \\ y_t \\ nce_t \end{bmatrix} = \Sigma_j^p B_j \begin{bmatrix} z_{t-p} \\ y_{t-p} \\ nce_{t-p} \end{bmatrix} + \begin{bmatrix} + & + & 0 \\ + & + & + \\ * & * & - \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \eta_t \\ \nu_t \end{bmatrix} \tag{5}$$

2. The sign restrictions identify the noise shocks but do not distinguish between the persistent and the transitory shock. To separately identify the persistent shock from the transitory shock, I use what is referred to in the literature as the *max-share* identification strategy. I extract the persistent shock as the innovation that accounts for the maximum forecast error variance (FEV) share of utilization adjusted TFP at a long but finitie horizon. This method builds on Uhlig et al. (2004) and has been used by Francis et al. (2014) to identify long run TFP shocks. More recently this has been used by Kurmann and Sims (2021) in context of news shocks.

To formalize the identification strategy described above, let $j \in \{1, 2, 3\}$ be the structural shocks, and $i \in \{1, 2, 3\}$ denote TFP, GDP growth and nowcast error respectively. Define $I_{-j} = 1, \dots, k$ as a subset of the shocks of interest. Let s_{jh} be the sign restrictions on the impulse response vector to the j^{th} structural shock at horizon h. In this case, the impulse response is given by the j^{th} column vector of $\mathbf{IR}^h = \mathbf{C}_h(\mathbf{B})\mathbf{\Sigma_{tr}Q}$. The sign restrictions are represented by $\boldsymbol{S}_j(\boldsymbol{\phi})\boldsymbol{q}_j \geq \mathbf{0}$, for $j \in \mathcal{I_S}$. Let $CEFEV_j^i(H)$ denote the factor error variance (% contribution) at horizon H of variable i explained by the j^{th} structural shock.

$$CEFEV_j^i(H) = q\prime_j \Gamma h^i(\phi) q_j \quad ; \quad \boldsymbol{\Gamma}_{\boldsymbol{H}}^i(\boldsymbol{\phi}) = \frac{\Sigma_{h=0}^H c_{ih}(\phi) c'_{ih}(\phi)}{\Sigma_{h=0}^H c'_{ih}(\phi) c_{ih}(\phi)} \tag{6}$$

where $\boldsymbol{\Gamma}_{\boldsymbol{H}}^i(\boldsymbol{\phi})$ is $n \times n$ positive semi-definite matrix.

Thus, the identification of the three shocks, $\boldsymbol{Q}_{1:k} = [\boldsymbol{q}_1, \boldsymbol{q}_2, \dots, \boldsymbol{q}_k]$ requires us to solve the following problem

$$\boldsymbol{q}_1^* = \arg\max_{\boldsymbol{q}_1} \boldsymbol{q}_1' \boldsymbol{\Gamma}_{\boldsymbol{H}}^1(\boldsymbol{\phi}) \boldsymbol{q}_1 \tag{7}$$

subject to

$$\boldsymbol{q}_1'(1,3) = 0 \tag{8}$$

$$\boldsymbol{S}_j(\phi)\boldsymbol{q}_j \geq \boldsymbol{0}, \text{ for } j \in \mathcal{I}_{\mathcal{S}} \tag{9}$$

$$q_1' q_1 = 1 \tag{10}$$

Here the horizon is assumed to be $H = 40$ quarters, which is a medium run horizon. This is because the effects of transitory and noise shocks are not expected to persist for as long as a decade.[5] Now, this implies that the shock can only be extracted till 2012. To extend the series, for 2012-2019, I calculate H as the maximum available horizon from that point. In 2017, this is set to $H = 20$. As seen in Appendix Figure A7, persistent shocks explain the maximum variance of TFP even at 20 quarters. Equation 8 is the restriction that noise shocks have zero effect on TFP, which follows from the definition of the noise shock. Equation 9 consists of the sign restrictions detailed in equation 5. Equation 10 ensures that the identified shocks are mutually orthogonal. I follow the algorithm outlined by Carriero and Volpicella (2022) to solve this optimization problem. I assume 4 lags as suggested by the Akaike Information Criterion and uniform priors.

The impulse response of the nowcast errors to the identified shocks suggest that forecasters do not have full information about the economy. Appendix Figure A6 shows the impulse response of TFP, GDP growth and nowcast errors to the identified persistent, transitory and noise shocks. The nowcast error increases on impact of the persistent shock but does not recover immediately in the next period. Furthermore, the nowcast error responds weakly to the transitory shock on impact and has a delayed positive response. This signifies that forecasters cannot distinguish immediately if a shock is persistent, transitory or noise and learn with some persistence. Noise shocks have a negative effect on impact on the nowcast errors since this is a restriction imposed by the VAR.

Predictably, the positive persistent shock increases TFP as on impact and declines persistently. GDP growth weakly responds to a persistent productivity shock on impact, but has a delayed positive and persistent response. A transitory shock increases TFP and GDP growth on impact but the effect is not persistent. Finally, TFP does not respond to noise shocks, in line with the zero restriction imposed. The Noise shock has a positive and somewhat persistent effect on GDP growth.

3.1 Effect of Noise Shocks on Labor Market Dynamics

Key labor market variables exhibit significantly persistent impulse responses to the identified noise shocks at the business cycle frequency (8-10 quarters). A historical decomposition shows that noise shocks have an increasingly important role to play in the evolution of unemployment, vacancies and job finding rates over the business cycle, which is a motivation to introduce imperfect information in a search and matching model.

[5] The results are robust to longer horizons, up to $H = 60$ quarters.

Smooth Local Projections Once the shocks are extracted from the VAR, I can now study how labor market variables respond to these shocks using smooth local projections (SLP) (Barnichon and Brownlees, 2019). For each shock u_j, the Jordà (2005) local projections are given by

$$y_{t+h} = \alpha_h^j + \beta_h^j u_t^j + \sum_{p=1}^{P} \gamma_p^j \omega_{t-p} + \mu_{h,t+h}^j \tag{11}$$

where ω_{t-p}^j is the set of lagged values of y and u^j.

Following Barnichon and Brownlees (2019), one can approximate $\beta_h^j \approx \sum_{k=1}^K b_k^j B_k^j(h)$ using a linear B-splines basis function expansion in the forecast horizon h. Thus, the corresponding smooth Linear Projections can be wriiten as Equation 12.

$$y_{t+h} \approx \sum_{k=1}^{K} a_k^j B_k(h)^j + \sum_{k=1}^{K} b_k^j B_k^j(h) u_t^j + \sum_{p=1}^{P} \sum_{k=1}^{K} c_{pk}^j B_k^j(h) \omega_{t-p}^j + \mu_{h,t+h}^j \tag{12}$$

The SLP is estimated using generalized ridge estimation and further details can be found in Appendix section A.5 and Barnichon and Brownlees (2019).

Here, y_t = aggregate labor market outcomes such as unemployment rate, vacancies, rate of outflow from unemployment (*UE*), job-to-job transition rates (*EE*), hiring rate and wage growth. u^j are the three shocks respectively while μ_t^j is the residual error for each regression. All labor market data are from Current Population Survey and JOLTS for vacancies and hiring rate.[6] Figures 3 and 4 show the impulse responses of the labor market variables to standardized 1 standard deviation negative noise and persistent TFP shocks.[7]

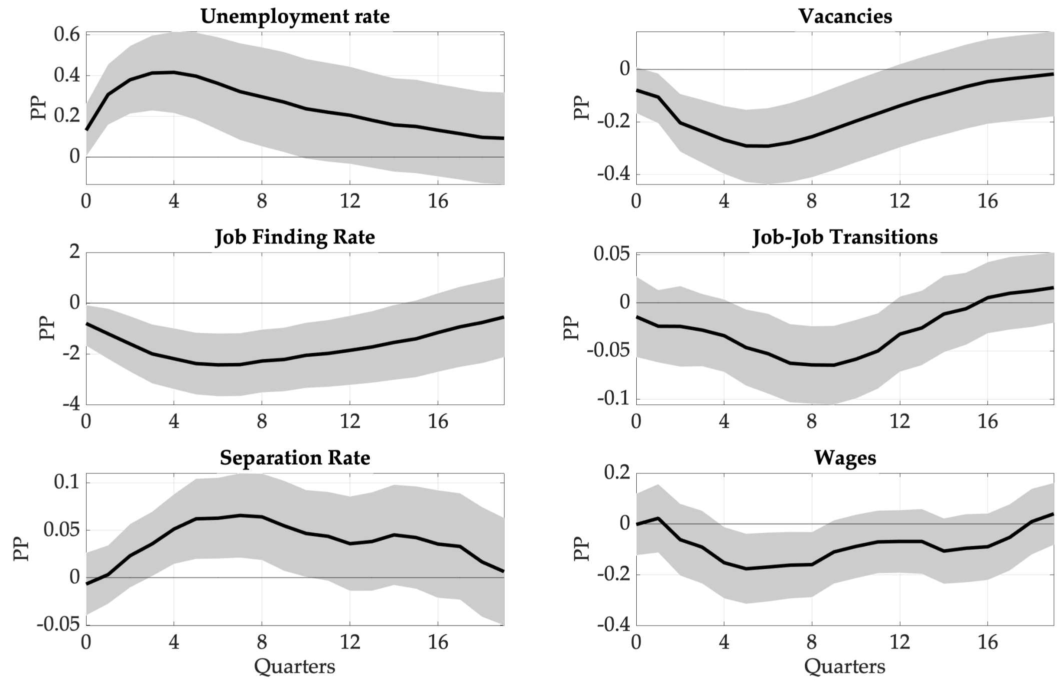
Noise shocks have a significant and persistent effect on unemployment, vacancies, *UE*, *EE* as well as hiring rate for up to 10 quarters. The negative effect on wage growth is delayed, although weak, indicating that wages are sluggish. Unemployment rises by 0.6 percentage points in response to a one standard deviation noise shock. The number of job vacancies decreases, transitions from unemployment to employment reduce, and job-to-job transitions decline. As there are fewer vacancies, there are fewer number of jobs to be found, dampening the job-finding rate of the workers. Furthermore, as wage growth declines, there are fewer number of workers making job-to-job transitions. This further dampens job finding rates for the unemployed as jobs in lower end of the ladders remain occupied since fewer workers are moving up the ladder, making it harder for unemployed workers to find jobs. These ultimately lead to unemployment rate being higher for longer.

These results suggest that agents cannot distinguish the type of shock they face correctly and that they learn slowly over time about the true shocks. The hump shape of the impulse responses suggest that initially agents misperceive the noise shock as an actual negative productivity shock

[6] The results are consistent with using an Autoregressive Distributed Lag (ADL)pecification for local projections.

[7] Response to the transitory TFP shocks is documented in Appendix Figure A10.

Figure 3: Impulse Response to Noise Shocks



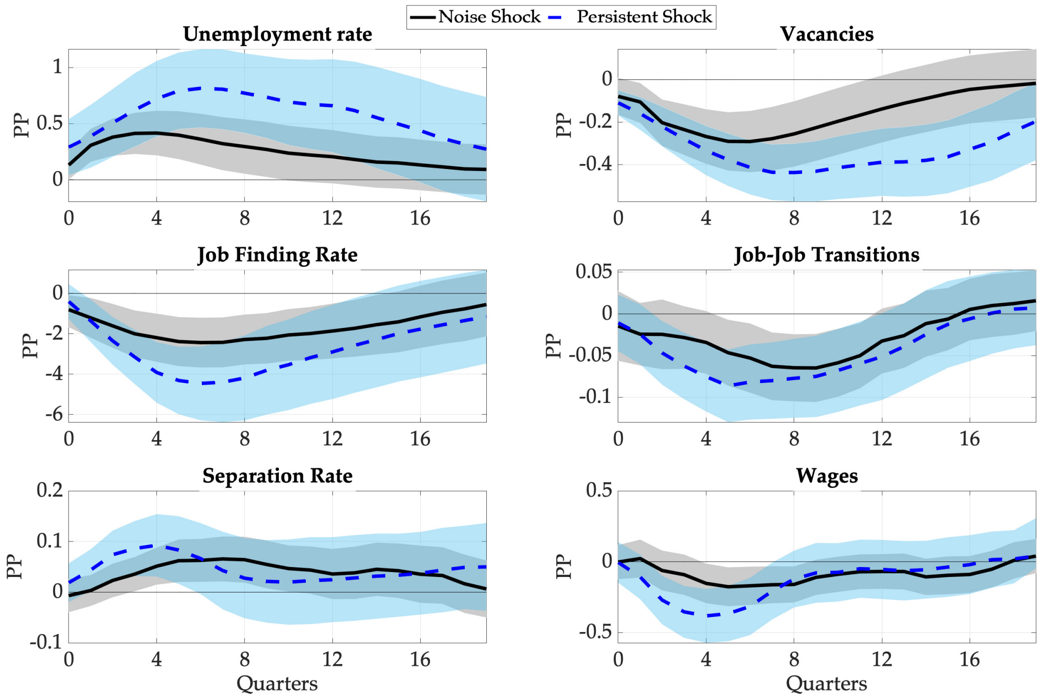
Note: This figure shows the smoothed cumulative impulse response functions for key labor market variables to a noise shock, estimated using equation 11, where u_j is the noise shock identified using the SVAR described by the optimization problem in equation 7. The sample period is 1968q4: 2019q4. Data for the labor market outcomes are from CPS, vacancies from Barnichon (2010a) and wages from BEA's average hourly earnings series. The shaded area represents a 95% confidence interval.

and hence respond as if faced with an actual negative productivity shock. Firms decrease their hiring and increase layoffs. As there are less jobs to be matched with now, the job finding rate decreases and translates to an increase in unemployment. However, as firms and workers learn about the true process in the economy, they place higher weight on the shock being a noise shock and gradually start increasing hiring. As a result, outflow from unemployment increase, resulting in a decline in unemployment.

These results are consistent with learning which motivates the introducing of imperfect information in a general equilibrium model of search and matching. If there was complete information in the economy firms and workers would not respond to noise shocks because these don't change the fundamental economic conditions. Moreover, the time it takes for the impulse responses to recover, suggests that this learning process is quite gradual. If learning happened more rapidly, the economy would adjust to noise shocks much faster.

Forecast Error Variance Decomposition The forecast error variance decomposition is informative of the variance in an outcome explained by each of the shocks at a specific horizon. I use the estimator proposed by Gorodnichenko and Lee (2020) for calculating the forecast error

Figure 4: Impulse Response to Persistent TFP Shocks



Note: This figure shows the smoothed cumulative impulse response functions for key labor market variables to a persistent TFP shock (in blue), estimated using equation 11, where u_j is the persistent TFP shock identified using the SVAR described by the optimization problem in equation 7. The 95% confidence interval is shaded in blue as well. It is superimposed on the IRFs from the noise shocks in Figure 3. The sample period is 1968q4: 2019q4. Data for the labor market outcomes are from CPS, vacancies from Barnichon (2010a) and wages from BEA's average hourly earnings series. The shaded area represents a 95% confidence interval.

variance decomposition with local projections. The forecast error for the h-period ahead value of an endogenous variable y_t is given by

$$f_{t+h|t-1} \equiv (y_{t+h} - y_{t-1}) - P[y_{t+h} - y_{t-1}|\Omega_{t-1}] \tag{13}$$

where $P[y_{t+h} - y_{t-1}|\Omega_{t-1}]$ is the projection of $y_{t+h} - y_{t-1}$ on the information set $\Omega_{t-1} \equiv \{\Delta y_{t-1}, \mu_{t-1}, \Delta y_{t-2}, \mu_{t-2}, \cdots\}$. The forecast errors due to innovations in μ can be decomposed as follows:

$$f_{t+h|t-1} = \psi_{\mu,0}\mu_{t+h} + \cdots + \psi_{\mu,h}\mu_t + v_{t+h|t-1} \tag{14}$$

where $v_{t+h|t-1}$ is the error term due to innovations orthogonal to $\{\mu_t, \mu_{t+1}, \cdots, z_{t+h}\}$ and Ω_{t-1}.

The share of variances explained by the contemporaneous and future innovations in μ_t to the total variations in $f_{t+h|t-1}$ can be defined as follows (Sims, 1980):

$$s_h = \frac{\text{var}(\psi_{\mu,0}\mu_{t+h} + \cdots + \psi_{\mu,h}\mu_t)}{\text{var}(f_{t+h|t-1})} \tag{15}$$

s_h in equation 15 is estimated using the coefficient of determination estimator for FEVDs as proposed by Gorodnichenko and Lee (2020). The result of this exercise is summarized in Table 2.

The FEVD analysis reveals that at a short-run horizon of 0 to 8 quarters, noise shocks are notably influential in accounting for the variability in key labor market metrics such as unemployment, job openings, inflows and outflows from unemployment, and rates of transitions between jobs. Specifically, at an 8-quarter average, noise shocks account for 34% of the variation in unemployment, 37% in job vacancies, 35% in the outflow rate from unemployment, 27% in employment-to-employment transitions, and 14% in wage growth.

Table 2: Forecast Error Variance Decomposition: Shorter Run Horizon

	Short Run			Medium Run		
	Horizon: 0-8 quarters			Horizon: 9-16 quarters		
	Persistent	Transitory	Noise	Persistent	Transitory	Noise
Unemployment	0.43	0.23	0.34	0.63	0.21	0.16
Vacancies	0.42	0.21	0.37	0.61	0.20	0.19
UE	0.38	0.27	0.35	0.63	0.20	0.17
EE	0.42	0.31	0.27	0.65	0.16	0.19
Wage Growth	0.61	0.25	0.14	0.92	0.05	0.03

Note: This table reports the average forecast error variance decomposition for U, V, $E-E$, $U-E$ and ΔW, estimated using equation 15, over a short run (0-8 quarters) and a medium run (8-16 quarters) horizon. Each row adds to 1. Noise shocks explain a significant variation in the labor market at a short run horizon. The sample period is 1968q4: 2019q4. Data for the labor market outcomes are from CPS, vacancies from Barnichon (2010a) and wages from BEA's average hourly earnings series.

While persistent factors generally make up a larger share, ranging from 38% to 61% across these indicators, and transitory factors contribute between 21% and 31%, the influence of noise shocks is substantial. Especially in terms of job vacancies and unemployment, noise shocks account for more than one-third of the observed variability, highlighting their significant role in short-term fluctuations in the labor market.

At a longer run horizon of 8-16 quarters, persistent shocks are the primary drivers of variance across all labor market indicators. Specifically, they account for 63% of the variation in unemployment, 61% in vacancies, 63% in the job-finding rate, 65% in job-to-job transitions (*EE*), and 92% in wage changes. Predictably, noise shocks show a comparatively modest influence, accounting for 15-19% of the variance in unemployment, vacancies, job-finding rate, and *EE* transitions, and 3% in wages. Transitory shocks play a less substantial role, contributing to less than 25% of the variance in unemployment, vacancies, *UE*, and *EE* transitions respectively, and only 5% in wage growth.

Historical Contribution of Noise Shocks. To understand the role of imperfect information over the business cycle, it is useful to understand how much of the deviation of the key labor market outcomes from their predicted path can be explained by the productivity shocks. If noise shocks are not important, the productivity shocks would explain almost all the fluctuations in these variables.

Here, the decomposition for $j = \{1, 2, 3\}$ shocks can be written as the following:

$$y_t - \bar{\Psi}_t = \sum_j \sum_{h=0}^{t-t_0} \beta_h \cdot \mu_{j,t-h} \tag{16}$$

where, $\bar{\Psi}_t$ is the pure deterministic component and y_t is various labor market outcomes such as unemployment rate, vacancy postings, job finding rate and average hourly earnings.

Two key facts emerge from the historical decomposition: first, that the productivity shocks alone fail to account for the persistence of unemployment rate post 1985, and second, that noise shocks have been playing an increasingly important role since 1990s. Figure 5a plots the deviation of unemployment rate from its predicted path due to the persistent and transitory productivity shocks alone. Thus, the remaining movement is explained by the noise shocks.

An examination of the recessions in 1990, 2001, and 2007-09 reveals that the productivity shocks are insufficient to completely explain the fluctuations in the unemployment rate, vacancy postings and job finding rates. The productivity shocks predicted a faster recovery across these recessions and a diminished peak during the Great Recession. Moreover, Figure 2b demonstrates that professional forecasters during the Great Recession anticipated unemployment rates that were both higher and more persistent than the actual unemployment rate.

Outflow from unemployment and vacancies follows a similar pattern, where the fundamental shocks do not fully explain the fluctuation as well as the speed of the recovery. Noise shocks dampened the job finding rates during the expansion in the 90s, but amplified the vacancy postings. There seems to be a disconnect between the effect of imperfect information during expansions on households and firms, but during the downturns, noise shocks consistently amplify the decline in both job finding rates as well as vacancy postings.

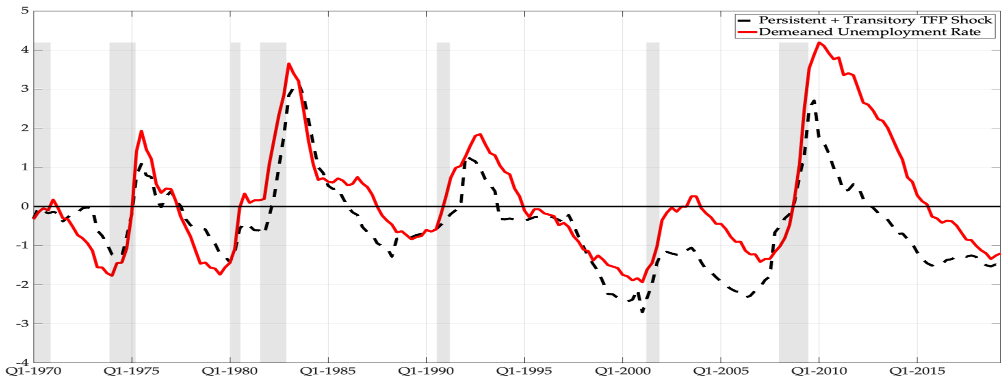
An aggregate assessment of these findings implies that during these recessions, noise shocks led to a mis-estimation of the persistence of the shock by economic agents. This misperception led to an overestimation of the actual persistence of the shock, thereby influencing decisions concerning employment and production. In other words, firms and workers perceived the recessions to be worse than they actually were. Consequently, there was a more pronounced reduction in vacancy postings, accompanied by a decrease in job-finding rates. These factors together resulted in unemployment levels that were not only elevated but also persistent, reflecting a persistence that was greater than originally anticipated.

To understand the contribution of the noise shocks to the persistence of unemployment, I compute for each recession between 1968-2019, the share of the rise in unemployment during the recession that has been reversed during the expansion following Equation 1

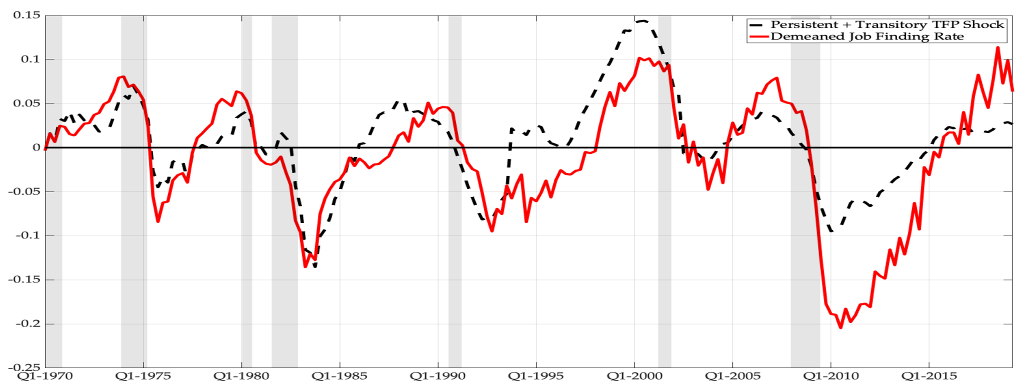
I then define persistence as the number of quarters to recover 50% of the rise in unemployment during a recession, that is $u_{recovery,t} = 0.5$. Now, from the historical decomposition, I can calculate what fraction of this persistence can be attributed to each of the shock by first computing the predicted unemployment rate from each shock and then calculating the persistence as defined above. The results are summarized in Appendix Table A1. For the great recession, noise shocks

Figure 5: Historical Contribution of Persistent and Transitory TFP Shocks

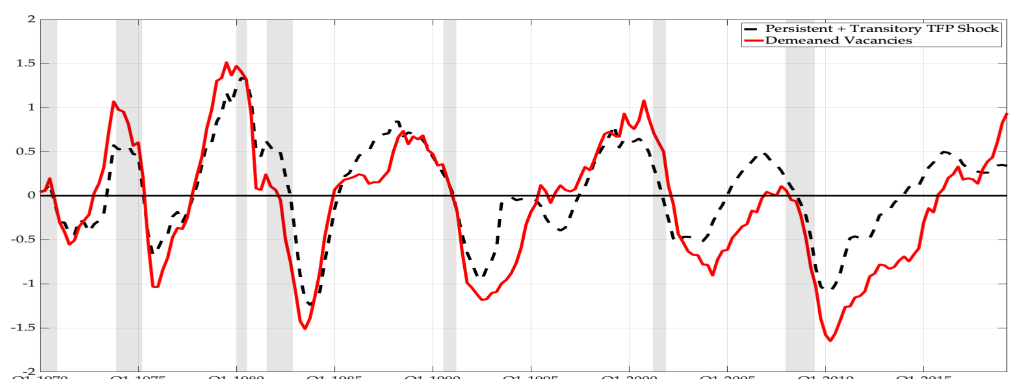
(a) Unemployment Rate



(b) Outflow from Unemployment



(c) Vacancies



Note: This figure shows the historical decomposition of unemployment rate, vacancy postings and outflow rate from unemployment following equation 16. The dashed black line is the cumulative contribution of the identified persistent and transitory TFP shocks to the movements in the demeaned vacancy postings (solid red line). The remaining movement is explained by the noise shocks, which contribute significantly to the vacancy postings during the recessions in 1990-91, 2001 and 2007-09.

account for about 35% of the 50% of the rise in unemployment and on average noise shocks account for 27% of this recovery across recessions.

The second observation that emerges from this analysis is that the role of noise shocks appears to be more prominent post the Great Moderation. Figure A5 plots the shock series retrieved from the VAR and as can be seen, the noise shocks during the three recessions post 1990 had a larger negative draw than in the pre 1990 decades. Interestingly, the persistent shock displays the opposite pattern. This merely demonstrates that noise shocks have had a larger role to play post 1990, although the time-series is not long enough to establish if this is a systematic pattern. Pre-2000 it took on average 26 quarters for the unemployment rate to recover to its pre-recession trough while after 2000 it took 32 quarters. On average, noise shocks explain 19% of this recovery duration pre-2000, and 36% of this duration for the post-2000 recessions.

The empirical results indicate that noise shocks play a significant role in explaining the dynamics of the labor market over the business cycle and specifically the sluggish recovery from recessions. Now, to understand the mechanism through which noise shocks affect the persistence of the labor market, I introduce imperfect information in a general equilibrium model of search and matching in the following section.

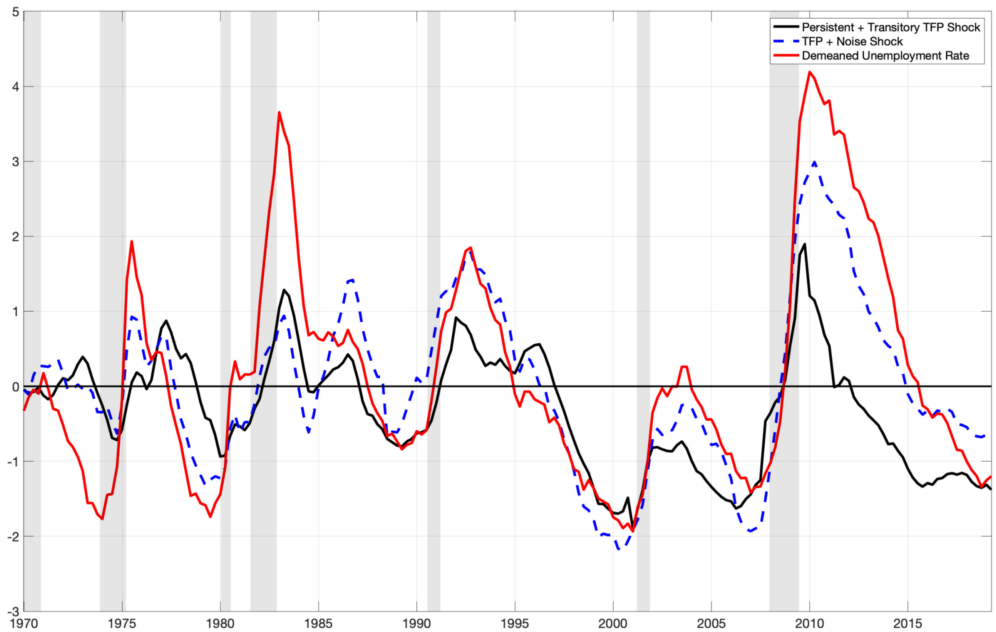
3.2 Robustness : Inclusion of Unrestricted Shocks

Structural shocks do not satisfy the sign restrictions for the noise shocks, since any structural shock results in a larger change in actual output than expected. However, there may be potentially other shocks such as monetary policy shocks or financial shocks, not included in the SVAR, which may behave like the noise shocks. To address this concern,I including a fourth unrestricted shock in the system. The key argument here is that if there are other shocks that are being picked up by any of the persistent, transitory or noise shocks, inclusion of the fourth shock should then account for those shocks. I include unemployment as the fourth variable and leave unrestricted the impact matrix. The modified VAR is thus given by equation 17.

$$\begin{bmatrix} z_t \\ y_t \\ nce_t \\ u_t \end{bmatrix} = \Sigma_j^p B_j \begin{bmatrix} z_{t-p} \\ y_{t-p} \\ nce_{t-p} \\ u_{t-p} \end{bmatrix} + \begin{bmatrix} + & + & 0 \\ + & + & + \\ * & * & - \\ * & * & * \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \eta_t \\ \nu_t \\ \mu_t \end{bmatrix} \tag{17}$$

Once again, I assume that ϵ_t maximizes the forecast error variance of TFP at a long run horizon. I present here the result of the historical decomposition exercise in Figure 6. Here as we see, the noise shocks still explain a significant variation in unemployment rate. However, in the 1973-75, as well as the 1980-81, 1982-83 recessions, the contribution of the 4th shock is the highest in explaining the movement in unemployment rate. This is consistent with the fact that these recessions were mostly explained by monetary policy shocks or oil shocks, which cannot be attributed to TFP shocks.

Figure 6: 4 Variable VAR: Historical Contribution of Shocks to Unemployment Rate



Note: This figure shows the historical decomposition of unemployment rate following equation 16. The black line is the cumulative contribution of the identified persistent and transitory TFP shocks to the movements in demeaned unemployment rate (red line). The dashed blue line is the contribution of the TFP shock and the noise shocks, which contribute significantly to the unemployment rate during the recessions in 1990-91, 2001 and 2007-09. The remaining movement here is explained by the 4th shock μ_t.

Finally, I conduct further robustness by controlling for various shocks when estimating the impulse response of labor market outcomes to the noise shocks. In Section A.7, I control for contemporaneous uncertainty shocks as well as its lags (Bloom, 2009), and find that the results are robust to it. The impulse response of labor market outcomes to a noise shock, when controlling for the uncertainty shock remains within the 90 percent confidence interval of the response without the control. Further, the shape of these responses remain unchanged and consistent with imperfect information.

4 A Search and Matching Model with Information Frictions

Standard models of search-and-matching fail to fully explain the volatility of unemployment and vacancies as well as the slow recovery of the labor market from recessions Cole and Rogerson (1999).[8] Motivated by the empirical evidence that imperfect information plays an important role in explaining these dynamics, this section introduces an imperfect information structure to a search

[8] As Cole and Rogerson (1999) note, the DMP model can account for business cycle facts only if the average duration of non-employment spell is nine months or longer, which is quite high than observed in the data.

and matching model.

The model is based on a real business cycle model with search and matching in the labor market as in Merz (1995) and Andolfatto (1996) and follows the extensions by Gertler et al. (2020) who introduce staggered wage contracting and allow for on-the-job search with variable intensity. The primary reason for introducing a staggered wage contracting in the context of this paper is that wage rigidity amplifies the role of imperfect information, as will become clear in the subsequent subsections (Chahrour and Jurado, 2018; Morales-Jiménez, 2022). The reason for introducing endogenous search effort as well as on-the-job search, is to capture the response coming from workers when faced with information frictions. Job-to-job transitions capture not only the cyclical wage gains, but also crowd out unemployed workers searching for a job, thus capturing an important moment of the labor market. In the following sub-sections I describe the environment for the model and discuss the problems of firms and households.

Environment There is a continuum of firms and workers, each of measure unity. Firms that post vacancies and workers looking for jobs meet randomly. The aggregate productivity in the economy is given by z_t. Idiosyncratic match quality is revealed once a worker and a firm meet. Match quality of a worker within the firm is either good (g) with probability ξ or bad (b) with probability $1-\xi$. The productivity of a bad match is a fraction ϕ of the productivity of a good match, where $\phi \in (0,1)$. The firms' effective labor force is

$$l_t = g_t + \phi b_t \tag{18}$$

The total number if unemployed workers is given by:

$$\begin{aligned}\bar{u}_t &= 1-\bar{n}_t-\bar{b}_t\\ \bar{n}_t &= \int_i n_t di\\ \bar{b}_t &= \int_i b_t di\end{aligned}$$

where $\bar{n}_t$ and $\bar{b}_t$ are the total number of workers in good and bad matches respectively across all firms, indexed by i.

Workers search for jobs when they are unemployed with endogenous search intensity ζ_u. Employed workers in a bad match also search on the job so that they can move up the ladder and match with a good job. They search with endogenous search intensity ζ_b. Workers searching on the job only transition to good jobs. If they are matched with another bad job, they stay in their current bad jobs and hence lateral moveemnts to other bad jobs are eliminated.[9] Search is costly

[9] As Gertler et al. (2020) explain, the expected gain from a lateral move is quantitatively trivial and can be ruled out with a small moving cost.

and the cost of searching is characterized by

$$c(\zeta_{jt}) = \mu(\zeta_{jt})^{\frac{1}{1+\omega}}$$

where, ζ_{jt} is the search intensity of unemployed workers ($j = u$) and employed workers in bad matches ($j = b$). There are two ways a match can be dissolved. First, firms and workers may receive an exogenous separation shock with probability $1-\sigma$. Workers who receive the separation shock become unemployed at the beginning of next period. Second, if the match is not destroyed, a worker in a bad match searches on the job. If she finds another job and accepts it, the worker moves to the new firm within the period and the match with the current employer is dissolved. The total efficiency units of search is therefore given by the search intensity weighted sum of searchers

$$\bar{s}_t = \zeta_{ut}\bar{u}_t + \sigma\zeta_{bt}\bar{b}_t$$

The aggregate number of matches are thus a function of the efficiency weighted number of searchers $\bar{s}_t$ and the number of vacancies $\bar{v}_t$:

$$\bar{m}_t = \Psi\bar{s}_t^{\alpha}\bar{v}_t^{1-\alpha}$$

where α is the elasticity of matches to units of search and Ψ is the matching efficiency. The probability that a unit of search leads to a match is given by

$$p_t = \frac{\bar{m}_t}{\bar{s}_t}$$

It follows that the probability that the match is good (p_t^g) or bad (p_t^b) is as follows respectively

$$\begin{aligned} p_t^g &= \xi p_t \\ p_t^b &= (1-\xi)p_t \end{aligned}$$

For a firm, the probability that a vacancy will lead to a match is:

$$q_t^m = \frac{\bar{m}_t}{\bar{v}_t}$$

Now, not all matches will lead to hires since I assume that workers in bad matches accept only good jobs. Thus, the probability that a vacancy leads to a good quality hire (q_t^g) or to a bad quality hire (q_t^b) is given by

$$\begin{aligned} q_t^g &= \zeta q_t^m \\ q_t^b &= (1-\zeta)\left(1-\frac{\sigma\zeta_{bt}\bar{b}_t}{\bar{s}_t}\right)q_t^m \end{aligned}$$

Since all workers accept good matches, q_t^g is simply the product of the probability of a match being good conditional on a match and the probability of a match. However, since workers in bad matches do not make lateral movements, the fraction of searchers who search on-the-job from bad matches, $\frac{\sigma\zeta_{bt}\bar{b}_t}{\bar{s}_t}$ is netted out to calculate q_t^b. Thus, the expected number of workers in efficiency units of labor that a firm can expect to hire from posting a vacancy as:

$$q_t = q_t^g + \phi q_t^b$$

Thus, the total number of new hires (in efficiency units) is $q_t v_t$ and the hiring rate χ_t is the ratio of new hires to the existing stock l_t, given by:

$$\chi_t = \frac{q_t v_t}{l_t}$$

We can now define some law of motions for the good and bad matches. respectively.

$$\bar{g}_{t+1} = \sigma\bar{g}_t + \xi p_t \bar{s}_t \tag{19}$$

$$\bar{b}_{t+1} = \sigma(1 - \zeta_{bt}(1-\xi)p_t)\bar{b}_t + (1-\xi)p_t\bar{u}_t \tag{20}$$

Total good matches next period are a sum of surviving good matches in the current period and an inflow of searchers into good matches, which depends on their probability of finding a good match. Similarly, total number of bad matches next period are a sum of two terms. the first term represents the number of workers in bad matches who are unable to find a good match and thus remain in the bad match. The second term is the number of unemployed workers who find bad matches and move into them. The current values of l_t, g_t and b_t are predetermined state variables.

The intra-period timing protocol that the firm's decision problem is based upon is: (i) realization of aggregate and firm-level shocks, (ii) wage bargaining and production, (iii) realization of match-level separation shocks, and (iv) search and matching. We can now look at the problems that the firms and workers face in the subsequent sub-sections.

Information Structure This section introduces an imperfect information structure which is analogous to the structural VAR deployed to recover the belief shocks as well as the persistent and transitory productivity shocks. The information structure aims to capture the fact that agents do not have full information about the state of the economy.

However, it is important to note that agents have rational expectations, given their information set. Agents do not perfectly know whether the current aggregate productivity, which is the only source of aggregate uncertainty, is persistent or transitory. They get a public signal about the persistent component and form expectations based on it. Let $z_t = logZ_t$. From now on, a lowercase variable will denote the log of the corresponding uppercase variable. x_t is the permanent component and η_t is the temporary component.

$$z_t = x_t + \eta_t \quad ; \quad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2) \tag{21}$$

x_t follows an AR(1) process:

$$x_t = \rho x_{t-1} + \epsilon_t \quad ; \quad \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2) \tag{22}$$

Each period, all agents in the economy observe a noisy signal $\hat{s}_t$ about the permanent component of the productivity process, which is given by

$$\hat{s}_t = x_t + a_t \tag{23}$$

$$a_t = \rho_a a_{t-1} + \nu_t \quad ; \quad \nu_t \sim \mathcal{N}(0, \sigma_\nu^2) \tag{24}$$

The shocks η_t, ϵ_t and ν_t are mutually independent. The noise term ν_t in the signal a_t prevents the agents from perfectly identifying permanent innovations to technology and generates variation in the agents' beliefs regarding x_t, independent of the fundamentals. It is a pure shock to expectations and does not affect productivity. Permanent shock to productivity is ϵ_t which affects aggregate productivity and also affects beliefs. The temporary shock η_t affects agents' beliefs and realized productivity in the first period and only affects beliefs in the subsequent periods.

Persistence in Noise. Here, the noise is assumed to be persistent. This serves the purpose of making the signal extraction problem more complex for the agents. Agents now not only cannot discern if a shock is persistent, transitory or noise, but they also cannot discern whether the persistence in change in productivity is attributed to a true persistent change in productivity or a persistent signal.

Let $x_{t|t} \equiv x_t \,\Big|\, \mathcal{I}^t$ denote the agents' expectations regarding x_t conditional on their information set at date t. This implies, $x_{t|t} \equiv \mathbb{E}_t[x_t]$. Agents update their beliefs about x_t in a Bayesian manner, using a Kalman filter.

Thus, the dynamics of $x_{t|t}$ is.

$$x_{t|t} = \rho_x x_{t-1|t-1} + \mathbf{K}_{t-1}(\mathbf{s}_t - \mathbf{s}_{t|t-1}) \tag{25}$$

where, $\mathbf{s}_t$ is the vector of signals ($\mathbf{s}_t = [z_t, \hat{s}_t]$), and $\mathbf{K}_t$ is the Kalman gain matrix. The details of the filtering process are in Appendix Section B.1.

Timing. Here, the timing of the signal and expectation formation is key, which is as follows:

1. Firms and workers form expectations at beginning of t with information set $\mathcal{I}^{t-1}$.

2. Firms and workers make their decisions for time period t.

3. Public signal is revealed as is the value of z_t. However, firms and workers do not learn from this signal in time period t (Pre-commitment).

Thus, agents make their decisions about time t outcomes based on the signal as well as the aggregate productivity they observed at the end of time period $t-1$. Now, a key point to note here is that technically, the agents in the model could observe various real outcomes in the economy such as $z_t, y_t, c_t, u_t, v_t, s_t, w_t$ and learn about the true aggregate productivity. However, assuming that that signal extractions is costly and agents only use the signal to learn and make decisions. This assumption is similar to Woodford (2001), Mankiw and Reis (2002) and Angeletos et al. (2020) where agents do not learn endogenously.

Assumption 1 *Firms and workers observe publicly available real variables in the model at time t, but do not include them in their information set $\mathcal{I}^t$ since this signal extraction is costly. Furthermore, all the information processing that the workers undertake to learn the state of the economy is summarized in the public signal a_{t-1}. Agents form their expectations at the beginning of the period before the signal is revealed for t and pre-commit to their decisions that they make in t, which are based on $\mathcal{I}^{t-1}$.*[10]

Firm's Problem There is a continuum of firms indexed with a mass normalized to 1. All firms produce a homogeneous good that is sold in a competitive market. The aggregate productivity in the economy is z_t with a transitory component η_t and a permanent component x_t about which the agents receive a noisy public signal. Firms produce with capital and labor, and their output can be used for consumption or for capital accumulation. Capital is perfectly mobile and firms rent capital on a period by period basis. Firms add labor through a search and matching process described above. The production function is $y_t = z_t k_t^{\zeta} l_t^{1-\zeta}$. Let the stochastic discount factor be $\Lambda_{t,t+1}$, w_t be the wage per efficiency unit of labor and r_t be the capital rental rate. I assume that labor recruiting costs are convex in the hiring rate of labor in efficiency units, χ_t.

The firms decision problem is therefore to choose χ_t to maximize the value of the firms which is the discounted stream of profits net of recruiting costs, wages and capital rental expenses, subject to the law of motion for l_t, g_t and b_t, and given the expected paths of wages and rental rate. Firm's solve the following problem:

$$F_t = \max_{k_t,\chi_t} \mathbb{E}_t \left\{ z_t k_t^{\zeta} l_t^{1-\zeta} - \frac{\kappa}{(1+\eta_h)} \chi_t^{(1+\eta_h)} l_t - w_t l_t - r_t k_t + \Lambda_{t,t+1} F_{t+1} \,\middle|\, \mathcal{I}^{t-1} \right\} \tag{26}$$

subject to the law of motions of l_t, g_t and b_t given in equations 18, 19 and 20. The first order conditions give us the rental rate of capital and a first order condition for hiring.

[10] This assumption can be thought of as economic data releases being lagged by one period. Firms and workers see the data release in t, which contain the information from $t-1$. This assumption tries to mimic this aspect. In the model, therefore, nowcast errors are analogous to the data nowcast errors.

$$(27) \qquad k_{t+1} \quad : \quad z_t \zeta \left(\frac{l_t}{k_t}\right)^{1-\zeta} - r_t = 0$$

$$(28) \qquad \chi_t \quad : \quad -\kappa(\chi_t)^{\eta_h} l_t + \mathbb{E}_t(\Lambda_{t,t+1} F_{t+1}) = 0$$

Given Cobb-Douglas production technology and perfect mobility of capital, k_t does not vary across firms. It is also important to note that while the firm pays the same recruitment costs for bad and good workers (in quality adjusted units), bad workers have different survival rates within the firm due to their incentive to search on-the-job. The first order condition for hiring rate can be solved to get the vacancies v_t since $\chi_t = q_t v_t / l_t$. Each firm optimizes their hiring rate and in equilibrium, total vacancies are given by summing across all firms, $\bar{v} = \int_0^1 v_i di$.

Household's Problem There is a unit measure of families, each with a measure one of workers. The family pools all wage and unemployment income. Consumption and savings decisions are made at the household level, but household members make their decisions based on the same information set $\mathcal{I}$. Each family owns diversified stakes in firms that pay out profits and assigns consumption $\bar{c}_t$ to members and saves in the form of capital $\bar{k}_t$, which is rented to firms at rate r_t and depreciates at the rate δ. The household solves the following problem,

$$(29) \qquad \Omega_t = \max_{\bar{k}_{t+1}, \bar{c}_t} \mathbb{E}_t \left\{ log(\bar{c}_t) + \beta \Omega_{t+1} \right\}$$

subject to

$$\begin{aligned}
\bar{c}_t + \bar{k}_{t+1} + c(s_t^b)\bar{b}_t + c(s_t^u)\bar{u}_t &= \bar{w}_t \bar{n}_t + \phi \bar{w}_t \bar{b}_t + \bar{u}_t u_B + (1 - \delta + r_t)\, \bar{k}_t + T_t + \Pi_t \\
\bar{g}_{t+1} &= \sigma \bar{g}_t + \xi p_t \bar{s}_t \\
\bar{b}_{t+1} &= \sigma(1 - \zeta_{bt}(1-\xi)p_t)\bar{b}_t + (1-\xi)p_t \bar{u}_t
\end{aligned}$$

Unemployed Workers Let U_t be the value of unemployment, V_t^g the value of a good match, and V_t^b the value of a bad match. u_B is the flow benefit from unemployment. An unemployed worker searches with an endogenous search intensity ζ_{ut}. The value of unemployment is given by:

$$(30) \qquad U_t = \max_{\zeta_t^u} \mathbb{E}_t \left\{ u_b - c(\zeta_{ut}) + \Lambda_{t,t+1} \left((1-p_t)\zeta_{ut} U_{t+1} + \zeta_{ut}(1-\xi)p_t V_{t+1}^b + \zeta_{ut} \xi p_t V_{t+1}^g \right) \middle| \, \mathcal{I}^{t-1} \right\}$$

Here, in the current period, an unemployed worker receives u_b, net of search costs. In $t+1$, With probability $(1-p_t)\zeta_{ut}$, an unemployed worker does not find a job and remains unemployed in $t+1$.[11] Unemployed workers find it optimal to accept either a bad or a good match if they receive one if the wages are greater than their outside option.

[11] The average value of employment in the continuation value of U_t should be that of a new hire rather than the unconditional one. However, Gertler and Trigari (2009) show that the two are identical up to a first order.

Employed Workers Employed workers earn a wage w_j while employed at firm j. The workers in a a bad match search on the job with endogenous intensity σ_{bt} and are matched with another firm with probability $\sigma_{bt}p_t$. However, I assume that employed workers only move up the ladder. They switch jobs only if they find a firm that offers a better continuation value. Employed workers are separated from their job with exogenous probability $(1-\sigma)$, in which case they have to spend at least one period in unemployment before they can be matched with another firm. The employed worker solves the following problem

Value of being employed for a worker in a good match is given by the following

$$V_t^g = \mathbb{E}_t\left\{ w_{gt} + \Lambda_{t,t+1}\left(\sigma V_{t+1}^g + (1-\sigma)U_{t+1}\right) \,\middle|\, \mathcal{I}^{t-1} \right\} \tag{31}$$

A worker in a good match earns wage w_{gt} while employed in a good match. Since there is no ladder to move up, these workers do not search on-the-job. In the next period, the worker can either get the separation shock in which case she flows into unemployment. Otherwise they continue being in a good match in the subsequent period.

Now, the value of being employed for a worker in a bad match is given by:

$$\begin{aligned} V_t^b = \max_{\zeta_{bt}} \mathbb{E}_t \Big\{ & \phi w_t - \sigma c(\zeta_{bt}) + \Lambda_{t,t+1}\Big(\sigma\zeta_{bt}(1-\xi)p_t V_{t+1}^b \\ & + \sigma\zeta_{bt}\xi p_t V_{t+1}^g + (1-\sigma)U_{t+1}\Big) \,\Big|\, \mathcal{I}^{t-1} \Big\} \end{aligned} \tag{32}$$

A worker in a bad match searches on-the-job and hence chooses their search intensity to optimize their value from a bad match. While in a bad match, the worker earns the wage w_{bt}, and if the worker survives within the firm, which occurs with probability σ, she searches with variable intensity ζ_{bt}, and since search is costly, they pay the cost of searching. In the next period, if they are hit by the separation shock they flow into unemployment. If they remain employed in the bad match, the worker might be matched with a good job in which case they move to the good job next period. If matched with another bad match, the worker chooses to stay in the current bad job.

Wage Contracts Workers and firms divide the joint match surplus via staggered Nash bargaining à la Gertler and Trigari (2009). The firm bargains with workers in good matches for a wage while workers in bad matches then receive the fraction of the wage for good workers, corresponding to their relative productivity.[12] Thus, when bargaining with good workers, firms also take account of the implied costs of hiring bad workers. For the firm, the relevant surplus per worker is:

$$J_t = \frac{F_t}{l_t}$$

[12]This wage rule for workers in bad matches approximates the optimum wage from direct bargaining.

For good workers, the relevant surplus is the difference between the value of a good match and unemployment:

$$H_t = V_t^g - U_t$$

The expected duration of a wage contract is exogenous. At each period, a firm faces a fixed probability $1-\lambda$ of renegotiating the wage and with λ probability, the wage from the previous period is retained. The expected duration of a wage contract is $\frac{1}{1-\lambda}$. Workers hired in between contracting periods receive the prevailing firm wage per unit of labor quality w_t. The wage w_t^N is chosen to maximize:

$$w_t^N = \arg\max_{w_t} \left\{ H_t(w_t)^{\eta} J_t(w_t)^{(1-\eta)} \,\middle|\, \mathcal{I}^{t-1} \right\} \tag{33}$$

subject to

$$w_{t+1} = \begin{cases} w_t \text{ with probability } \lambda \\ w_{t+1}^N \text{ with probability } 1-\lambda \end{cases} \tag{34}$$

where w_{t+1}^N is the wage chosen in the next period if there is renegotiation and η is the households relative bargaining power. Now, to a first order approximation, the evolution of average wages can be written as follows

$$\bar{w}_t = (1-\lambda)\bar{w}_t^N + \lambda \bar{w}_{t-1} \tag{35}$$

Here, the average wages and the average contract wage are defined by

$$\begin{aligned} \bar{w}_t &= \int_{w,\gamma} w dG_t(w,\gamma) \\ \bar{w}_t^N &= \int_{w,\gamma} w_t^N(\gamma) dG_t(w,\gamma) \end{aligned}$$

$dG_t(w,\gamma)$ denotes the time t fraction of units of labor quality employed at firms with wage less than or equal to w and ratio of bad-to-good workers less than or equal to γ.[13]

Resource Constraint To close the model, the resource constraint states that the total resource allocation towards consumption, investment, vacancy posting costs, and search costs is equal to aggregate output

$$\bar{y}_t = \bar{c}_t + \bar{k}_{t+1} - (1-\delta)\bar{k}_t + \frac{\kappa}{2}\int_i \varkappa_t^2 l_t di + c(s_t^b)\bar{b}_t + c(s_t^u)\bar{u}_t \tag{36}$$

[13]Under multi–period bargaining, the outcome depends on how the new wage settlement affects the relative surpluses of firms and workers in subsequent periods where the contract is expected to remain in effect. As shown in Gertler and Trigari (2009), up to a first order approximation, the contract wage will be an expected distributed lead of the target wages that would arise under period-by-period Nash bargaining, where the weights on the target for period $t+i$ depend on the likelihood the contract remains operative which is λ^i.

The government funds unemployment benefits through lump-sum transfers:

$$T_t + (1 - \bar{n}_t - \bar{b}_t)b = 0 \tag{37}$$

Equilibrium The aggregate state of the economy is defined by $\Omega = \{l, g, b, k, z, x^{\mathcal{T}}, n^{\mathcal{T}}\}$. A recursive equilibrium is characterized as a solution for a set of (i) value functions $\{J_t, V_t^g, V_t^b, U_t\}$, (ii) prices $\{r_t, w_t^N, w_{t+1}, \bar{w}_t, \bar{w}_t^N\}$, (iii) allocations $\{\chi_t, \zeta_{ut}, \zeta_{bt}, \bar{k}_{t+1}, \bar{c}_t, \bar{g}_t, \bar{g}_t\}$, (iv) the density function of composition and wages across workers dG_t, a transition function $Qt, t+1$, a law of motion for the economy Π_t, such that given the law of motion for exogenous variables z_t, x_t and n_t:

1. households optimize such that c_t, k_{t+1} satisfy the optimality conditions;
2. optimal search and hiring: $\zeta_{bt}, \zeta_{ut}, \chi_t$ optimize the Bellman equations for V_t^b, U_t, J_t;
3. wage w_t^N satisfies the Nash Bargaining Rule and w_{t+1} is given by 35;
4. all Markets Clear: Rental market of Capital clears, households optimize consumption and search intensities. Firms optimize on hiring decisions and capital investment;
5. $\bar{g}_t$ and $\bar{b}_t$ evolve according to their respective laws of motion and the evolution of G_t is consistent with the transition function $Q_{t,t+1}$;
6. at each point in time, agents' beliefs are determined by their information set $\mathcal{I}^{t-1}$, their perceived law of motion for the economy. Agents update their beliefs about the aggregate productivity in a Bayesian manner with the timing consistent with Assumption 1.

Special Cases

1. **Full Information Benchmark.** The goal of theoretical framework is twofold. First, to assess whether introducing imperfect information improves the prediction of duration of recovery of unemployment as compared to a full information framework. Second, to understand the propagation mechanism for imperfect information. For either scenario, it is important to define the full information benchmark. Under full information, the agents perfectly observe z_t and x_t each period along with other variables. Therefore, when making their decisions, the agents are fully aware of the state of the economy and can perfectly observe each component of aggregate productivity. Hence there are only two shocks in this case: persistent and transitory productivity shock. As there is no information friction, and they immediately adjust their expectations in response to any changes in the economy.
2. **Imperfect Information Without Noise.** Another important consideration is the role of imperfect information, even without noise shocks. In this framework, I assume that the information structure is the same as in the imperfect information with noise shocks framework, and agents observe z_t and a signal $\hat{s}_t$ about the persistent component of the aggregate productivity

Table 3: Parameter Values

Parameters	Interpretation	Value	Source
β	Discount rate	0.99	Shimer (2005)
δ	Depreciation rate	0.025	Gertler and Trigari (2009)
ζ	Production function parameter	0.33	Gertler et al. (2020)
ω	Elasticity of search cost	3.60	Faberman et al. (2022)
γ	Worker's bargaining power	0.5	Shimer (2005)
λ	Renegotiation frequency	0.75	Gertler et al. (2020)
α	Elasticity of matches to searchers	0.4	Gertler et al. (2020)
η_h	Hiring cost convexity	2.40	Merz and Yashiv (2007)
ρ_z	Technology autoregressive parameter	0.949	Shimer (2005)

Note: This table reports the parameter values that have been fixed to widely accepted external values in the literature.

x_t. Here, the noise shocks are never realized, but agents believe that there is some noise in the economy and adjust their expectations accordingly.

5 Parameterization and Estimation

I estimate the parameters in the model at a quarterly frequency using a three-step procedure. First, I fix the parameters $\{\beta, \delta, \zeta, \omega, \gamma, \lambda, \alpha, \eta_h, \rho_z\}$ to widely accepted values from the literature. Then, I estimate $\{\Psi, \kappa, \mu, \sigma, \phi, u_b, \xi\}$ by targeting some unconditional stationary moments using the simulated method of moments. Finally, the remaining parameters $\{\sigma_\epsilon, \sigma_n u, \rho_n, \mathcal{K}\}$ are estimated to match the impulse responses of unemployment rate, vacancies, outflow from unemployment, job-to-job transition rates, hiring rates and wage growth to the identified noise shocks as well as the persistent productivity shock in the data. Table 3 summarizes the result of the calibration strategy. I calibrate the output elasticity of labor $\alpha = 0.33$, the discount factor $\beta = 0.99$, and depreciation rate $\delta = 0.025$ to widely accepted values in the literature.

Targeting Unconditional Moments. As a first step, I target the steady state unemployment rate, unemployment-to-employment transitions, job-to-job transitions and separation rate in the model to match the average values from the United States for the period 1968-2019. I also target the flow value of unemployment, u_B, to match the relative value of non-work to work activity $\bar{u}_T = 0.71$ following Hall and Milgrom (2008).[14]

The efficiency parameter Ψ is targeted such that the steady state unemployment rate in the model matches the average unemployment rate from 1968-2019 in the data, and takes a value of 0.49. The hiring cost parameter κ determines the resources that firms invest into recruiting, and hence, influences the probability that a worker finds a job. I set the steady state job finding probability to match the quarterly *UE* transition probability, $\tilde{p} = 0.28$; and then calibrate κ to be consistent with

[14] The relative non-work to work satisfies EXPRESSION. The value of non-work includes saved search costs from on-the-job search and the value of work includes saved vacancy posting costs.

Table 4: Unconditional Targeted Moments

Parameters	Interpretation	Value	Target
Ψ	Match efficiency	0.49	Unemployment Rate = 0.055
κ	Cost of hiring	7.21	$U - E = 0.28$
μ	Scale parameter of search cost	0.082	$E - E = 0.025$
$1 - \sigma$	Separation rate	0.010	$E - U = 0.010$
ϕ	SS productivity from bad job	0.76	Average E-E wage increase = 0.045
ξ	Probability of finding a good job	0.24	Average wage-improv. flow share = 0.53
u_b	Flow value of unemployment	2.43	Relative value, non work = 0.71

Note: This table reports the parameters estimated using Simulated Method of Moments to target some key stationary moments in the data. These moments are: unemployment rate, unemployment to employment transition rate, job-to-job transition rate, employment to unemployment separation rate and wage change of workers who make job to job transitions. These moments are calculated over the sample period 1968q4 - 2019q4 using the CPS.

$\tilde{p}$. Furthermore, a higher search cost implies a lower *EE* probability and hence, the search cost parameter μ is targeted to match *EE* probability, and takes a value $\mu = 0.082$. The separation rate σ is targeted to match the E-U probability. The steady state productivity from a bad job, ϕ is targeted to match the change in wage of workers who make job-to-job transitions. The ratio of bad jobs to good jobs is held constant and is calibrated following Gertler et al. (2020).[15] I further calibrate ζ to match the average share of job transitions involving positive wage changes out of total job flows and target this number to be 0.527, following Gertler et al. (2020). The corresponding value if $\zeta = 0.23$. A lower probability of finding a good job corresponds to a higher steady state value of bad-to-good workers, and hence a higher average share of bad-to-good flows. Finally, the hiring cost convexity η_h is targeted to match

Information Parameters: Impulse Response Matching. I estimate the information parameters by matching model-implied responses following a noise shock, and TFP shock to their counterparts in the empirical exercise (Rotemberg and Woodford, 1997; Christiano et al., 2005). The targets are the responses of unemployment rate, *UE* rate and *EE* rate for horizons of up to 20 quarters. The impulse response matching is done by minimizing the distance between the model-generated impulse response functions (IRFs) and the empirical IRFs. Let f, be the column vector stacking the point estimates of each of these impulse responses, where $i = 1, \cdots, N$ indexes the different IRFs, and h is the horizon at which the IRFs are being evaluated. The model-generated IRFs are denoted as $f_m(\Theta)$, where Θ is a vector of model parameters. The optimization problem is given as:

$$\min_{\theta} \,(f - f_m(\Theta))' \, W \,(f - f_m(\Theta)) \tag{38}$$

15

$$\frac{\bar{b}}{\bar{g}} = \frac{(1-\lambda)(p^{EE} + p^{EU})}{p^{EE} + \lambda p^{EU}}$$

where p^{EE} and p^{EU} are probability of E-E transitions and E-U transitions respectively

Table 5: Estimated Parameters from IRF Matching

Parameters	Interpretation	Estimate	Std. Error
σ_ϵ	Std. Dev of Persistent TFP shock	0.062	0.009
σ_ν	Std. Dev of Noise Shock	0.096	0.007
ρ_n	Noise Autoregressive Parameter	0.921	0.004
$\mathcal{K}$	Signal-to-Noise Ratio	0.23	0.003

Note: This table reports the estimated parameters from the impulse response matching exercise outlined in equation 38. The third column reports the estimated values while the fourth column reports the standard errors for these values. The impulse responses are matched by GMM and the standard errors are calculated using the delta method.

where, $\Theta = \sigma_\epsilon^2, \sigma_\nu^2, \rho_n, \mathcal{K}$, where $\mathcal{K}$ is the signal-to-noise ratio. The weight matrix W is the inverse of the variance-covariance matrix of the empirical IRF estimates.[16]

The result of this estimation process is documented in Table 5, with standard errors calculated using the delta method (Guerron-Quintana et al., 2017). The signal-to-noise ratio is 0.23 , which is low as the noise shocks have a large variance. Thus, the implied standard deviation of the transitory productivity shock is found to be $\sigma_\eta = 0.192$, which is relatively large compared to the standard deviation of the noise shock as well as that of the persistent TFP shock, so that learning about the persistent component of productivity is gradual. This implies that the agents in the economy learn quite slowly about the true persistent TFP component.

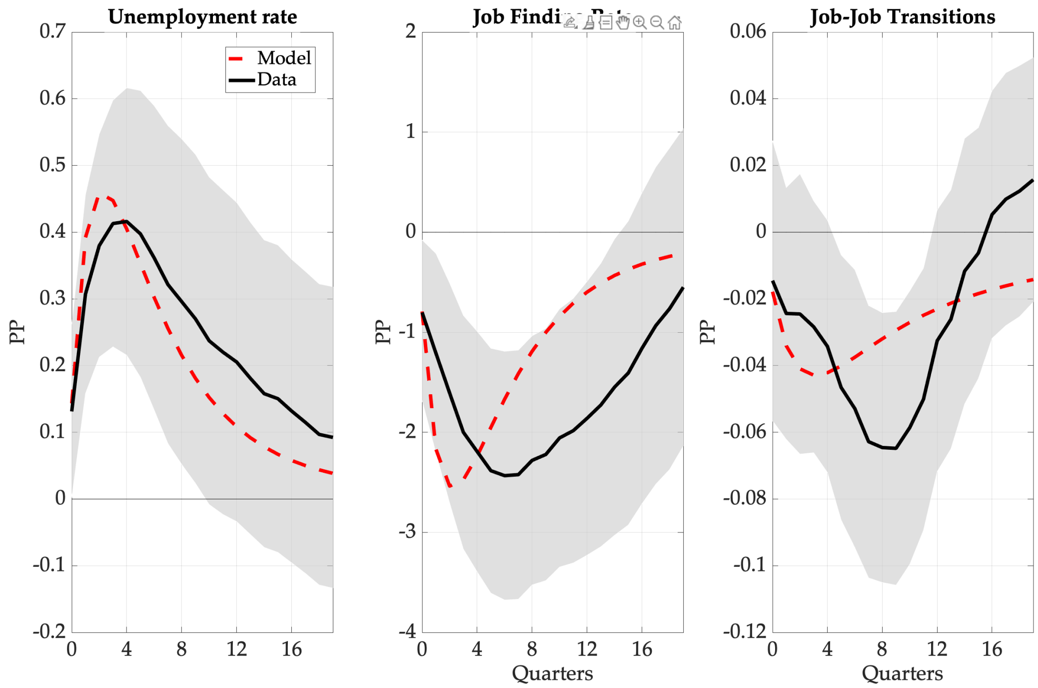
Figures 7 plots the impulse responses from the empirical exercise and the impulse responses implied by the estimated model in response to a noise shock and a persistent TFP shock. The model fit is good, with all the model implied impulse responses falling within the confidence bands from the empirical exercise. The impact as well as the dynamics for unemployment rate, job finding rate and job-to-job transitions matches the empirical impulse responses well. The dynamics for vacancies and hiring rate are not matched well as the model fails to capture the curvature which the empirical impulse responses display.

The benchmark model for the rest of the paper is the imperfect information model with noise shocks. I consider several counterfactual models. The first is the full information model which is re-calibrated as discussed in Appendix Section B.2. In this framework, firms and workers perfectly observe z_t, x_t every period and immediately revise their expectations. The second framework, is the imperfect information model without noise shocks. This model is not re-calibrated. Here, firms and workers still have imperfect information and do not observe x_t, but only see the signal $\hat{s}_t$ each period. However, the noise shocks are never realized. This model serves as an important comparison to highlight the role of imperfect information.

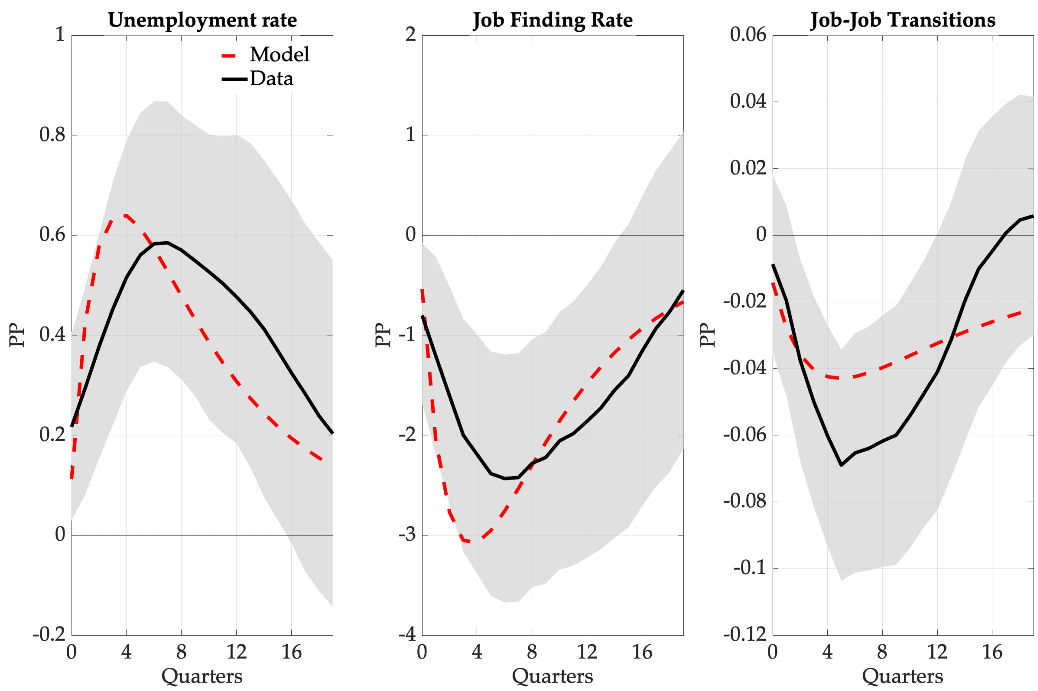
Business Cycle Statistics To understand how the model with imperfect information performs with respect to the observed business cycle statistics in the data, I report the volatility and correlation

[16]The objective function becomes a form of the generalized method of moments estimator. In this case, the optimization problem aims to match moments (the IRFs) in a way that is efficient given the variability of the empirical estimates.

Figure 7: Impulse Responses from Data and Estimated Model



(a) Noise Shocks



(b) Persistent TFP Shock

Note: This figure shows the results of IRF matching for noise shocks and persistent TFP shocks.

of several labor market outcomes with output in Table 6. The table compares the business cycle statistics obtained by simulating the benchmark model and the full information model, to the statistics in the US economy from 1968-2019 for unemployment rate (U), job vacancies (V), job-tp-job transitions (EE), job transitions from unemployment to employment (UE), and hiring rate.

While both models offer reasonable approximations of output data, the imperfect information model outperforms the full-information model across all other variables, both in terms of standard deviation and correlation with output and is closer to empirical observations. It's worth

Table 6: Business Cycle Statistics

	Data		Full Information		Imperfect Info. without Noise		Imperfect Info. withNoise	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
x	SD	corr(Y,x)	SD	corr(Y,x)	Info	corr(Y,x)	SD	corr(Y,x)
Y	0.019	1	0.019	1	0.021	1	0.024	1
U	0.162	-0.859	0.092	-0.742	0.117	-0.768	0.152	-0.792
V	0.182	0.702	0.131	0.642	0.157	0.675	0.196	0.728
EE	0.102	0.720	0.067	0.629	0.071	0.661	0.088	0.825
UE	0.069	0.734	0.044	0.639	0.058	0.653	0.077	0.692
Hiring Rate	0.058	0.677	0.034	0.571	0.036	0.622	0.042	0.723

Note: This table reports standard deviation of key labor market variables and their correlation with output in the model. The data here has been simulated from the model and HP-filtered (100,00).

acknowledging that the full-information model already incorporates features like wage rigidity and on-the-job search—factors known to induce volatility in search models (Shimer, 2005). Yet, the introduction of imperfect information augments the volatility of unemployment by an additional 23% relative to the full-information benchmark. Similarly, the imperfect information framework yields higher volatility for job vacancies and transition rates. This underscores the imperfect information model's enhanced efficacy in capturing the dynamics of labor markets.

Forecast Error Variance Decomposition The identified nosie shocks explain about a third of the variance in the labor market at a short run horizon. To understand how the benchmark model compares to the observed moments, I report the forecast error variance decomposition calculated by simulating the imperfect information model, in Table 7, for 8 quarters. The benchmark model can match the forecast error variances of the key labor market outcomes observed in the data reasonalbly well. The model predicts that the noise shocks explain 31% of the forecast error variance in unemployment rate which is 90% of the forecast error variance in the data explained by noise shocks. On average, the model overpredicts the forecast error variance by 7%.

Table 7: FEVD: Data and Model

	Data			Model		
	Horizon: 0-8 quarters			Horizon: 0-8 quarters		
	Persistent	Transitory	Noise	Persistent	Transitory	Noise
Unemployment	0.43	0.23	0.34	0.48	0.21	0.31
Vacancies	0.42	0.21	0.37	0.49	0.19	0.32
Job-finding Rate	0.38	0.27	0.35	0.42	0.21	0.37
E-E	0.42	0.31	0.27	0.49	0.17	0.34
Wages	0.61	0.25	0.14	0.60	0.22	0.18

Note: This table reports the forecast error variance in the model with imperfect information and compares it to the moments in the data.

6 Role of Imperfect Information in Labor Market Dynamics

The benchmark model with information frictions is not only a good fit to the data, as seen in the previous section, but also predicts higher volatility in the labor market than the model with full information. Now, the identified noise shocks played an important role in explaining the slow recovery of unemployed in the data. In this section, I first explain a propagation mechanism of shocks under imperfect information in the benchmark model. After establishing the mechanism, I document a counterfactual exercise to demonstrate that imperfect information can contribute significantly to the slow recovery of unemployment rate in recessions. Finally, I discuss the importance of various other channels such as sticky wages and on-the-job search, which have been proposed as possible channels for generating higher persistence in search and matching models.

6.1 Mechanism for Propagation of Shocks under Imperfect Information

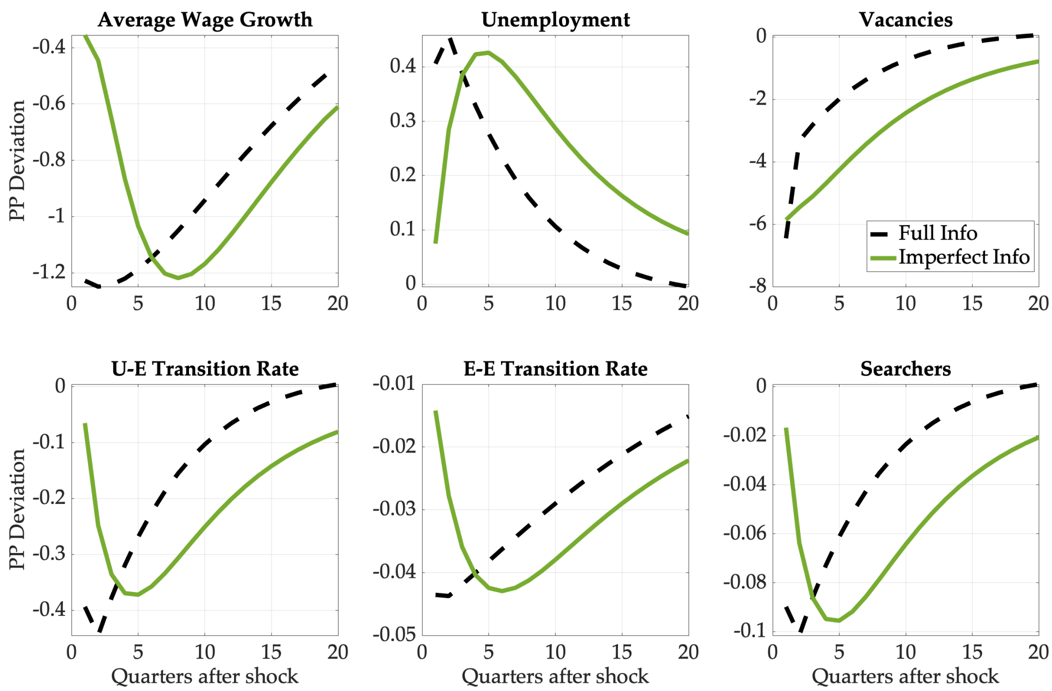
Figure 8 illustrates the effect of a one standard deviation negative persistent productivity shock on key outcomes. The solid lines represent the imperfect information framework, while the dashed lines are the full information benchmark. In an environment characterized by imperfect information, agents—both firms and workers—operate under a Bayesian learning framework where they assign probabilistic weights to shocks as either persistent, transitory, or mere noise.

The uncertainty surrounding the nature of these shocks induces a form of temporal inertia in agent responses. Due to sticky wages, firms and workers do not immediately adjust wages as much as in the full information benchmark. This initial under-reaction stems from the fear that if the shocks are transitory or merely noise, an increase in wages would be sub-optimal when subsequently productivity levels decline, thereby reducing the future discounted profits.

In contrast to a full-information benchmark where responses are immediate and unambiguous, under imperfect information, we observe a moderated initial decrease in key labor market variables such as job vacancies, job-to-job transitions, and *UE* transitions.

However, as firms and workers update their beliefs about the change in productivity, they

Figure 8: Impulse Response to a Positive Persistent TFP Shock



Note: This figure shows the impulse response functions for the re-calibrated full information model (dashed black line) and the imperfect information model (solid green line) to a negative 1 standard deviation persistent TFP shock.

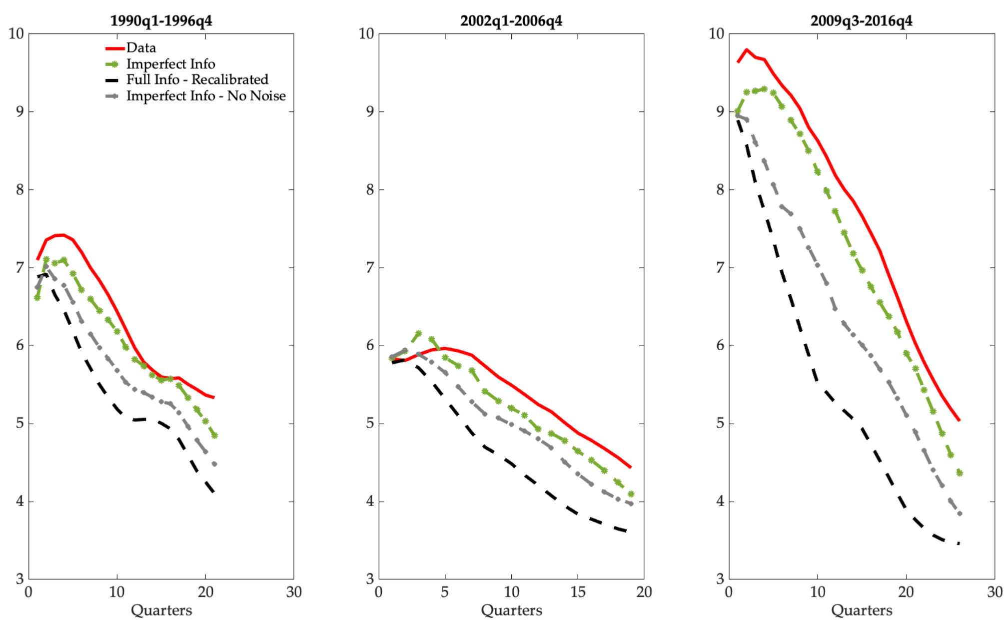
assign more weight each period to the change being truly persistent, and we see a more pronounced adjustment mechanism. This adjustment in expectations is significantly slowed down by the persistence in the noise as agents face a more complex signal extraction problem. As the firms and workers put more weight on the shock being persistent, the firms that get a chance to renegotiate now offer lower wages and as a result the average wage decreases. This triggers decrease in search intensity for both unemployed and employed workers, as workers now anticipate lower wages and thus lower surplus from a match. Further, firms post fewer vacancies as they now place more weight on the shock being a true negative persistent shock. Consequently, this generates sluggishness in the job-finding rate. Eventually, unemployment starts increasing in a hump-shaped trajectory and we observe a more persistent response in unemployment than the full information framework.

This illustrates the importance of sticky wages in propagating the imperfect information. If wages were flexible, they could keep adjust immediately as agents learn about the nature of the shock, and recovery would be faster. Further persistence is generated by the on-the-job search, as employed workers crowd out the unemployed workers in bad matches, and also cause firms to post fewer vacancies. This significantly delays the job-finding process for the unemployed workers, thus contributing to the persistence of unemployment. With the combination of sticky wages, on-the-job search and imperfect information, persistent productivity shocks have significantly more persistent effects on unemployment than would under the full information framework.

6.2 Unemployment Dynamics across Recessions: Data vs Model

In this section, I simulate the calibrated imperfect information model to generate counterfactual unemployment rate series for 5 recessions between 1970-2019. This exercise shows that imperfect information explains the slow recovery of the unemployment rate, specially in the last three recessions. For this exercise, the model is normalized to match the starting unemployment rate for each of the recessions. While simulating the imperfect information model with noise, all three identified shocks from the VAR are incorporated each period. For the imperfect information model without noise, only the persistent and transitory shocks from the VAR are incorporated each period. For the full information model, I introduce the persistent and the transitory shocks each period. Furthermore, the full information model is re-estimated as described in the previous section, to match the empirical IRFs to the persistent productivity shocks. The estimated parameters for the full information model are presented in the Appendix.

Figure 9: Model Implied Recovery of Unemployment for Recessions Post 1990s



Note: This figure shows the model implied, simulated unemployment rate for the re-calibrated full information model (dashed blue line), the imperfect information model without noise (gray line) and the imperfect information model (solid green line) for the Great Recession, 2001 recession and the 1990-91 recession.

The imperfect information model predicts the persistence of the unemployment rate for the three recessions post 1990 quite well. In contrast, the full information model predicts much faster recoveries. For the Great Recession, the actual unemployment rate took 37 quarters to recover to its pre-recession trough. The imperfect information predicts the recovery at 32 quarters whereas the full information model predicts a much faster recovery at 24 quarters. In other words, the imperfect information model predicts almost 33% slower recovery than the full information benchmark.

For the 2001 recession, the duration of recovery for unemployment was 24 quarters, and the imperfect information model (20 quarters) predicts 25% slower recovery than the full information model (16 quarters). In 1991 recession, the unemployment recovery took 28 quarters. The imperfect information model predicted a recovery at 22 quarters, almost 38% higher than the full information benchmark which predicted recovery at 16 quarters. This highlights the contribution of imperfect information to the persistence of the labor market. Larger noise shocks further dampen the economy as firms and workers perceive a negative productivity shock to be more persistent than it actually is. The slow learning by agents combined with sticky wages, translates into a slower recovery.

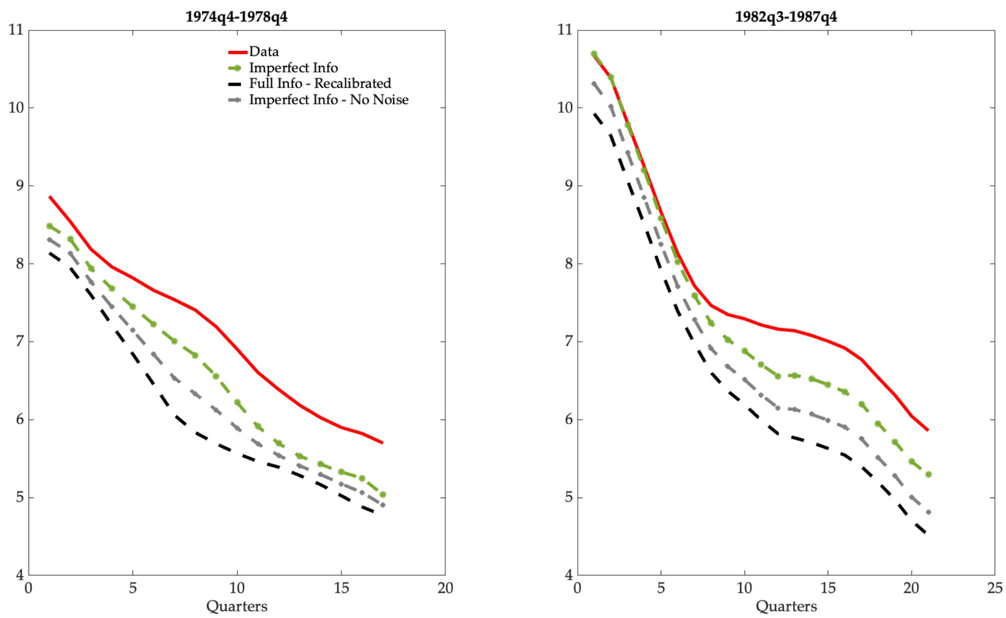
For the pre-90s recessions, the full information and the two imperfect information models are comparable in their prediction for recovery of unemployment rate. This is because the noise shocks identified in the SVAR play a much smaller role in explaining the fluctuations in the labor market. With smaller noise shocks, the agents' perceived productivity, while still lower than actual, was not too far off from the true productivity. Thus, the imperfect information models predict similar recovery relative to the full information model. To be precise, in the 1981-82 recession (14 quarters), the imperfect information model with noise shocks predicted recovery in 11 quarters while the full information model predicted recovery in 9 quarters. For the 1973-78 recession (23 quarters), the imperfect information model with noise shocks predicted recovery in 17 quarters while the full information model predicted recovery in 14 quarters. The results are also summarized in Appendix Table B2.

6.2.1 Model Decomposition: Sticky Wages, On-the-job Search and Imperfect Information

In this section, I compare the persistence of unemployment under various mechanisms with and without imperfect information. In this model, there are three factors that add to the persistence of the unemployment rate: on-the-job search, sticky wages and learning. To understand the contribution of each channel, I compare a full information benchmark to imperfect information model under 4 scenarios: a) flexible wages without on-the-job search b) flexible wages with on-the-job search, c) sticky wages without on-the-job search, and d) sticky wages with on-the-job search.

The measure of persistence I use is the average number of quarters across recessions to recover 50% of the rise in unemployment during recession. I calculate for each recession between 1968-2019, the share of the rise in unemployment during the recession that has been reversed during the expansion following Equation 1. For each recession, I calculate the average number of quarters it takes from the beginning of the recession to recover 50% of the rise in unemployment. Empirically, it took 17 quarters from the beginning of the recession to recover 50% of the rise in unemployment across recessions between 1968-2019. To highlight that learning contributes to persistence under each specification, I plot this measure in Figure 11. In the stacked bar graph, I

Figure 10: Model Implied Recovery of Unemployment for Recessions Pre 1990s



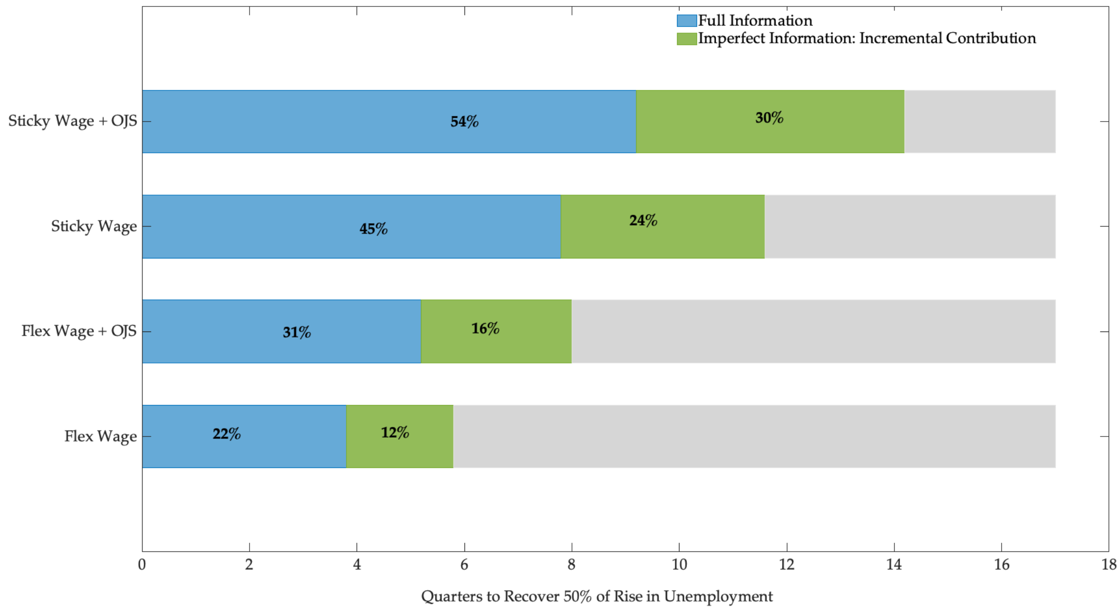
Note: This figure shows the model implied simulated unemployment rate for the re-calibrated full information model (dashed blue line), the imperfect information model without noise (gray line) and the imperfect information model with noise shocks (solid green line) for the Great Recession, 2001 recession and the 1990-91 recession.

re-calibrate the full information model as discussed in Section B.2.

Role of sticky wages. Sticky wages generate persistence in the labor market by making wage adjustment sluggish. As wages are slower to adjust downwards during recessions, incentive for firms to hire workers remains low. Thus, hiring declines and results in a lower job-finding rate with higher unemployment for longer than if the wages were flexible to adjust. Introduction of sticky wages with no on-the-job search contributes significantly to the persistence of unemployment, and under full information, it accounts for 45% (7 quarters) of the 50% of the rise in unemployment.

Role of on-the-job search. During downturns, on-the-job search creates congestion for the unemployed workers as the pool of employed workers in bad matches increases. This is because the incentive for employed workers to move up the ladder is low due to lower productivity. And as the probability of finding a good job is exogenously low, unemployed workers have fewer vacant low productivity jobs to move into and thus, finding a job takes longer, creating persistence in the unemployment rate. Furthermore, employed workers search with lower intensity due to which the firms post fewer vacancies and thus also dampens the unemployed workers probability of finding a job. When on-the-job search is introduced to a flex wage full information model, it predicts about 30% (5 quarters) of the duration to recover 50% of the rise in unemployment rate. When on the job search interacts with sticky wages, the full information model predicts about 54% (9 quarters) of

Figure 11: Average Duration to Recover 50% of Rise in Unemployment Across Models



Note: This figure shows the model implied duration to recover 50% of the rise in unemployment from the beginning of the recession, averaged across recessions between 1968-2019 for various model specification. The percentages are the percent of the data (18 quarters) that the particular model specification explains, while the x-axis is the actual number of quarters explained by the particular specification. The green bars are incremental contributions by learning, which implies that the total contribution of the imperfect information model is the sum of the blue and the green bar. Here, the full information model is re-calibrated as discussed in Section B.2. Further, I shut down each mechanism one by one in both models.

the persistence observed in the data.

Role of imperfect information. The previous two paragraphs highlighted that both on-the-job search and sticky wages endogenously generate persistence, predicting the unemployment rate to recover 50% of its rise in 10 quarters. To understand how much does imperfect information add to the persistence, we must look at the contribution coming from learning across all the model specifications. During downturns, due to noise shocks, firms and workers perceive the aggregate productivity shocks to be more persistent than they are. Since they only learn over multiple periods whether a shock is persistent or transitory, this generates a sluggishness as they keep behaving as if facing a negative productivity shock which is more persistent than the true shock. Firms anticipate lower returns from hiring while workers decline their search effort, leading to lower number of matches for as long as they learn about the true shock. When introducing imperfect information to the the flexible wages without on-the-job search framework, persistence increases, predicting the unemployment to recover 50% of it's rise in 6 quarters (35% of the total duration).

Learning interacts with on-the-job search and generates an additional 16% to the persistence of unemployment, predicting the 50% of the recovery in 8 quarters. Here, the employed workers are learning slowly about the true shock and they anticipate the productivity to be persistently worse than actual. Employed workers search effort remains dampened, which leads firms to post fewer vacancies and thus also dampens the unemployed workers chances of finding a job. This leads to dampened job finding rates for longer and hence higher duration of recovery of unemployment rate.

Learning interacts with sticky wages and generates higher persistence even without on-the-job search. Firms anticipate the productivity to be persistently worse than actual, which decreases their incentives to hire which is further amplified by wages which are slow to adjust downwards. Therefore, hiring remains dampened as they slowly learn about the true shock. Workers also decrease search effort and combined with lower hiring, this leads to dampened job finding rates and hence unemployment rate takes much longer to recover. Imperfect information with sticky wages predict that it would take 11 quarters to recover the 50% of the rise in unemployment. This is 65% of the recovery duration in the data and is 24% higher than the full information sticky wage model.

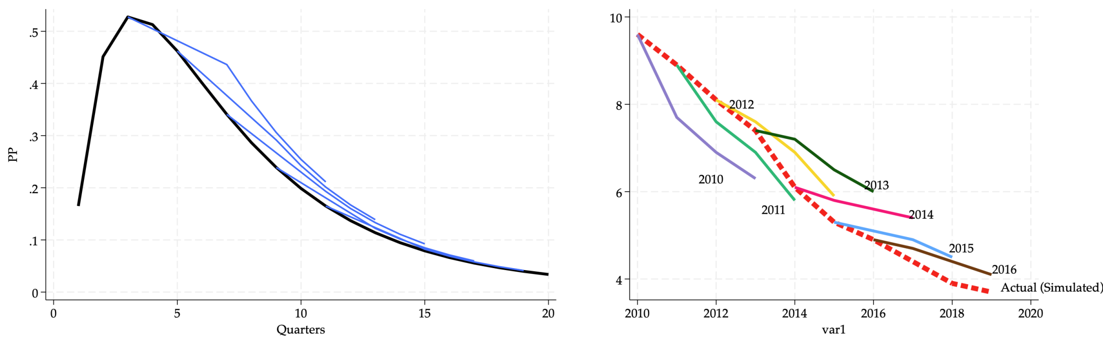
Finally, I show that imperfect information with sticky wages and on-the-job search adds a substantial 5.5 quarters (30%) to the average duration to recover 50% of the rise in unemployment, as compared to the full information counterpart. In equilibrium, as firms and workers anticipate the productivity to be persistently lower than actual due to imperfect information, sticky wages decline the incentives to hire even further, while decline in on-the-job search makes it harder for unemployed workers to find jobs, thus endogenously generating 84% of the persistence observed in the data.

In Appendix Section B.5.2, I discuss the model decomposition, comparing the full information model with the imperfect information model without noise shocks. This analyses establishes that learning endogenously leads to higher persistence of unemployment, even without noise shocks. In the model with sticky wages and on-the-job search, imperfect information adds 18% to the persistence of unemployment rate (approximately 3 quarters). This highlights the importance of incorporating imperfect information in models of search and matching to accurately predict the duration of recovery of unemployment from recessions.

6.2.2 Unemployment Forecasts in the Model.

The model presents a unique feature with respect to the unemployment forecast. When faced with a persistent productivity shock, due to imperfect information, agents attribute a part of the shock to be noise as well as transitory shock and hence their projections under-react to the actual unemployment rate. However, the reverse happens when they face a noise shock. Agents attribute some part of a negative noise shock to be persistent or transitory productivity and hence initially forecast the unemployment rate to be higher than it actually is (since true productivity has not changed). They eventually start placing more and more weight on the shock being noise and as they learn, their forecasts converges to the true unemployment rate. This is illustrated in Figure 12 where Panel (a) shows the 4-8 quarter ahead unemployment forecasts by agents in the model in response to a noise shock along with the impulse response of unemployment rate. Panel (b) shows the response of actual and forecasted unemployment rate in response to a persistent TFP shock.

Figure 12: Long-Run Unemployment Projections in the Model



(a) Response of Unemployment to Noise Shock (b) Unemployment Projections: Great Recession

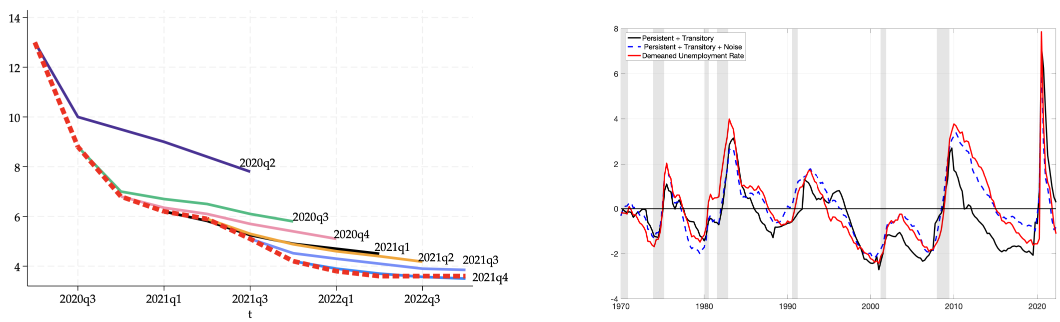
Note: Panel (a) shows the model implied 4-8 quarters ahead projections in response to a noise shock. The solid thick black line is the actual response of unemployment due to the shock. Panel (b) shows the model implied forecasts for unemployment rate 1,2 and 3 years ahead. The dashed black line is the model simulated unemployment rate for the Great Recession. While simulating the model, each period all three shocks act.

To illustrate that the noise shocks in this model can replicate the over-shooting of unemployment projections observed in the data, I simulate the model and generate long run forecasts. Figure 12b shows the model generated, one, two and three year ahead unemployment projections in the model after the Great Recession. Here, all three shocks, identified from the VAR, act together each period while simulation the imperfect information model with noise shocks. Since all three shocks act, the projections under-react if the contribution of the persistent shock dominates the contribution of the noise shocks as well as transitory shocks. Similarly, as the contribution of the noise shocks dominates, the projections over-estimate the unemployment rate. As seen in the historical decomposition of the unemployment rate in the data in Figure A11, the contribution of the noise shocks to the movement in unemployment dominates after 2012. Thus, in the model, initially, as the productivity shocks have higher weight, the unemployment rate is under-estimated by the agents in the model. However, from 2012, the contribution of the noise shocks increases but the agents are unable to discern the shock from a true persistent productivity shock and hence keep expecting higher unemployment rates in the future. However, as the shock is truly noise, the actual unemployment rate is lower than expected. This is similar to the pattern seen in the data in Figure 2b. It is important to note that the noise shocks are unique in generating over-estimation of long run unemployment projections. For all structural shocks, the long run expectations under-estimate the unemployment rate. Thus, noise shocks can be a potential solution to the consistent pattern observed in the data where the long-run unemployment forecasts are over-estimated by professional forecasters.

6.2.3 Unemployment Dynamics during COVID-19 Recession

Finally, I consider the recovery from the Covid-19 recession, which stands out as one of the quickest recoveries in postwar history. The unemployment rate rose from 3.5% in February 2020 to a peak of 14.7%, and declined to 3.9% at the end of 2021. The rise in unemployment was primarily due to temporary layoffs. Typically, unemployment from temporary layoffs declines quickly once economic activity improves as workers can to return to work quickly when labor demand improves. To understand the role of imperfect information, I first look at the shorter horizon expectations (1-4 quarters ahead) of the professional forecasters in Figure 13a, and the longer horizon expectations (1-3 years ahead) in Figure A2b. Forecasters revised their shorter horizon expectations much faster by 2021q4 and the longer horizon projections by 2021, suggesting that they expected this recession to be transitory relative to other recessions. In our framework, this suggests that the role of noise shocks was not very high during the Covid-19 recession. To formally understand the role

Figure 13: COVID-19: Projections and Contribution of Shocks



(a) Shorter Horizon Projections

(b) COVID-19: Historical Contribution of Shocks to Unemployment Rate

Note: Panel (a) shows the median 1-4 quarters ahead projections of unemployment rate from the Survey of Professional Forecasters during Covid-19. Panel (b) shows the historical decomposition of unemployment rate following equation 16. The black line is the cumulative contribution of the identified persistent and transitory TFP shocks to the movements in demeaned unemployment rate (red line). The dashed blue line is the contribution of the TFP shock and the noise shocks.

of imperfect information, I extend the SVAR by including the Covid 19 pandemic in my sample (1968-2022). Now, the max-share identification assumes that the persistent TFP shock maximizes the FEV of TFP at a long run. However, given that the Covid-19 pandemic happened less than 20 quarters ago, I assume that the persistent shock maximizes the forecast error variance of TFP even in the short run. However, since the identification of noise shocks does not depend on the max-share identification, this exercise is still informative about the dynamics of unemployment rate driven by noise shocks. In Figure 13b, the noise shocks did not play an important role in this recession, as most of the fluctuation is picked up by the TFP shocks. This can be explained due to the expectations that adjusted very quickly to the recovery and in the short run, forecasters predicted a transitory recovery. This suggests that noise shocks did not play an important role and although there was some degree of misperception, it was less than in other recessions such as 2007-09. In this case, the fundamental shocks contributed to most of the rise and the quick recovery.

7 Conclusion

This paper assess the role of imperfect information in labor market fluctuations and recovery patterns. Using a tri-variate structural VAR model, I identify noise shocks and their significant effects on labor market dynamics. I document that noise shocks can be an important driver of the slow recovery of unemployment during recessions. I find that without noise shocks, the labor market would have recovered faster by 7 quarter on average in the downturns between 1968-2019. Furthermore, noise shocks account for one-third of the variance in unemployment, job finding rate, and vacancy postings at the business cycle frequency. The response of labor market outcomes to the identified noise shocks is significant at the business cycle frequency and is hump-shaped. The quantitatively and statistically significant response to noise shocks suggest the presence of information frictions and the hump-shape indicates that firms and workers are learning under imperfect information. These results then motivate the introduction of imperfect information into a general equilibrium model of search and matching.

The introduction of imperfect information in a general equilibrium model provides a more robust framework for explaining the phenomena observed in the labor market. The model is calibrated to match unconditional moments in the data as well as the impulse responses to the identified shocks from the SVAR. The imperfect information model with noise shocks predicts ~ 30 percent higher persistence in recovery of unemployment on average across recessions, relative to the model with full information. During downturns, firms and workers receive a sequence of all the shocks, agents overestimate the persistence of the negative productivity shock due to presence of noise shocks and perceive the negative productivity shock to be persistently worse than it actually is. Since they gradually learn whether a shock is persistent or transitory, they respond as if facing a more persistent negative productivity shock than the true shock. Firms therefore post fewer vacancies for longer and workers search with lower intensity, which leads to persistently dampened job finding rates. This leads to a slower decline in unemployment rate, which is further exacerbated by sticky wages which are sluggish to adjust initially as well as due to on-the-job search. Finally, the imperfect information model with noise shocks predicts 23% higher volatility in the labor market indicators. This is particularly true for the period after 1990, emphasizing the increased importance of imperfect information in more recent economic conditions.

References

David Andolfatto. Business cycles and labor-market search. *The American Economic Review*, pages 112–132, 1996.

George-Marios Angeletos and Jennifer La'o. Noisy business cycles. *NBER Macroeconomics Annual*, 24(1):319–378, 2010.

George-Marios Angeletos, Luigi Iovino, and La'O Jennifer. Learning over the business cycle: Policy implications. *Journal of Economic Theory*, 190:105115, 2020.

Rudiger Bachmann. Understanding the jobless recoveries after 1991 and 2001. *Unpublished Manuscript, University of Notre Dame*, 2012.

Regis Barnichon. Building a composite help-wanted index. *Economics Letters*, 109(3):175–178, 2010a.

Regis Barnichon. Productivity and unemployment over the business cycle. *Journal of Monetary Economics*, 57(8):1013–1025, 2010b.

Regis Barnichon and Christian Brownlees. Impulse response estimation by smooth local projections. *Review of Economics and Statistics*, 101(3):522–530, 2019.

Paul Beaudry and Franck Portier. An exploration into pigou's theory of cycles. *Journal of monetary Economics*, 51(6):1183–1216, 2004.

David Berger et al. Countercyclical restructuring and jobless recoveries. *Manuscript, Yale*, 2012.

Olivier J Blanchard, Jean-Paul L'Huillier, and Guido Lorenzoni. News, noise, and fluctuations: An empirical exploration. *American Economic Review*, 103(7):3045–70, 2013.

Nicholas Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

Pedro Bordalo, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. Overreaction in macroeconomic expectations. *American Economic Review*, 110(9):2748–82, 2020.

Andrea Carriero and Alessio Volpicella. Generalizing the max share identification to multiple shocks identification: an application to uncertainty. 2022.

Ryan Chahrour and Kyle Jurado. News or noise? the missing link. *American Economic Review*, 108 (7):1702–36, 2018.

Ryan Chahrour, Sanjay K Chugh, Tristan Potter, et al. *Anticipated Productivity and the Labor Market*. Boston College, 2020.

Ryan Chahrour, Kristoffer Nimark, and Stefan Pitschner. Sectoral media focus and aggregate fluctuations. *American Economic Review*, 111(12):3872–3922, 2021.

Lawrence J Christiano, Martin Eichenbaum, and Charles L Evans. Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of political Economy*, 113(1):1–45, 2005.

Harold L Cole and Richard Rogerson. Can the mortensen-pissarides matching model match the business-cycle facts? *International Economic Review*, 40(4):933–959, 1999.

Fabrice Collard, Harris Dellas, and Frank Smets. Imperfect information and the business cycle. *Journal of Monetary Economics*, 56:S38–S56, 2009.

Antonello D'Agostino, Caterina Mendicino, and Federico Puglisi. Expectation-driven cycles and the changing dynamics of unemployment. *Journal of Money, Credit and Banking*, 54(7):2173–2191, 2022.

Wouter J Den Haan and Georg Kaltenbrunner. Anticipated growth and business cycles in matching models. *Journal of Monetary Economics*, 56(3):309–327, 2009.

Rochelle M Edge, Thomas Laubach, and John C Williams. Learning and shifts in long-run productivity growth. *Journal of Monetary Economics*, 54(8):2421–2438, 2007.

Zeno Enders, Michael Kleemann, and Gernot J Müller. Growth expectations, undue optimism, and short-run fluctuations. *Review of Economics and Statistics*, 103(5):905–921, 2021.

R Jason Faberman, Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa. Job search behavior among the employed and non-employed. *Econometrica*, 90(4):1743–1779, 2022.

Renato Faccini and Leonardo Melosi. Pigouvian cycles. *American Economic Journal: Macroeconomics*, 14(2):281–318, 2022.

John Fernald. A quarterly, utilization-adjusted series on total factor productivity. Federal Reserve Bank of San Francisco, 2014.

Mario Forni, Luca Gambetti, Marco Lippi, and Luca Sala. Noisy news in business cycles. *American Economic Journal: Macroeconomics*, 9(4):122–52, 2017.

Neville Francis, Michael T Owyang, Jennifer E Roush, and Riccardo DiCecio. A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks. *Review of Economics and Statistics*, 96(4):638–647, 2014.

Masao Fukui, Emi Nakamura, and Jón Steinsson. Women, wealth effects, and slow recoveries. *American Economic Journal: Macroeconomics*, 15(1):269–313, 2023.

Mark Gertler and Antonella Trigari. Unemployment fluctuations with staggered nash wage bargaining. *Journal of political Economy*, 117(1):38–86, 2009.

Mark Gertler, Christopher Huckfeldt, and Antonella Trigari. Unemployment fluctuations, match quality, and the wage cyclicality of new hires. *The Review of Economic Studies*, 87(4):1876–1914, 2020.

Yuriy Gorodnichenko and Byoungchan Lee. Forecast error variance decompositions with local projections. *Journal of Business & Economic Statistics*, 38(4):921–933, 2020.

Pablo Guerron-Quintana, Atsushi Inoue, and Lutz Kilian. Impulse response matching estimators for dsge models. *Journal of Econometrics*, 196(1):144–155, 2017.

Robert E Hall and Marianna Kudlyak. Why has the us economy recovered so consistently from every recession in the past 70 years? *NBER Macroeconomics Annual*, 36(1):1–55, 2022.

Robert E Hall and Paul R Milgrom. The limited influence of unemployment on the wage bargain. *American economic review*, 98(4):1653–1674, 2008.

Sebastian Heise, Fatih Karahan, and Ayşegül Şahin. The missing inflation puzzle: The role of the wage-price pass-through. *Journal of Money, Credit and Banking*, 54(S1):7–51, 2022.

Cosmin Ilut and Hikaru Saijo. Learning, confidence, and business cycles. *Journal of Monetary Economics*, 117:354–376, 2021.

Nir Jaimovich and Henry E Siu. Job polarization and jobless recoveries. *Review of Economics and Statistics*, 102(1):129–147, 2020.

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182, 2005.

Kathryn Koenders, Richard Rogerson, et al. Organizational dynamics over the business cycle: a view on jobless recoveries. *Review-Federal Reserve Bank of Saint Louis*, 87(4):555, 2005.

André Kurmann and Eric Sims. Revisions in utilization-adjusted tfp and robust identification of news shocks. *The Review of Economics and Statistics*, 103(2):216–235, 2021.

Andresa Lagerborg, Evi Pappa, and Morten O Ravn. Sentimental business cycles. 2020.

Guido Lorenzoni. A theory of demand shocks. *American Economic Review*, 99(5):2050–84, 2009.

N Gregory Mankiw and Ricardo Reis. Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics*, 117(4):1295–1328, 2002.

Yusuf Mercan, Benjamin Schoefer, and Petr Sedláček. A congestion theory of unemployment fluctuations. *American Economic Journal: Macroeconomics*, Forthcoming, 2023.

Monika Merz. Search in the labor market and the real business cycle. *Journal of monetary Economics*, 36(2):269–300, 1995.

Monika Merz and Eran Yashiv. Labor and the market value of the firm. *American Economic Review*, 97(4):1419–1431, 2007.

Kurt Mitman and Stanislav Rabinovich. Do unemployment benefit extensions explain the emergence of jobless recoveries? 2019.

Camilo Morales-Jiménez. The cyclical behavior of unemployment and wages under information frictions. *American Economic Journal: Macroeconomics*, 14(1):301–31, January 2022. doi: 10.1257/mac.20180404. URL https://www.aeaweb.org/articles?id=10.1257/mac.20180404.

Irina B Panovska. What explains the recent jobless recoveries? *Macroeconomic Dynamics*, 21(3): 708–732, 2017.

Julio J Rotemberg and Michael Woodford. An optimization-based econometric framework for the evaluation of monetary policy. *NBER macroeconomics annual*, 12:297–346, 1997.

Edouard Schaal. Uncertainty and unemployment. *Econometrica*, 85(6):1675–1721, 2017.

Robert Shimer. The cyclical behavior of equilibrium unemployment and vacancies. *American economic review*, 95(1):25–49, 2005.

Christopher A Sims. Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, pages 1–48, 1980.

Konstantinos Theodoridis and Francesco Zanetti. News shocks and labour market dynamics in matching models. *Canadian Journal of Economics*, 49(3):906–930, 2016.

Harald Uhlig. What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419, 2005.

Harald Uhlig et al. What moves gnp? In *Econometric Society 2004 North American Winter Meetings*, number 636. Econometric Society, 2004.

Michael Woodford. Imperfect common knowledge and the effects of monetary policy. Technical report, National Bureau of Economic Research, 2001.

Randall Wright. Job search and cyclical unemployment. *Journal of Political Economy*, 94(1):38–55, 1986.

A Empirical Appendix

A.1 Data Sources

This subsection describes all the data sources used in this paper. The sample period for all the primary analysis is 1968q4 to 2019q4.

1. Unemployment rate and unemployment to employment transition rates are constructed from the Current Population Survey (CPS).

2. Since 1994, the CPS has asked individuals whether they still work at the same job as in the previous month. However, it is not possible to observe job-to-job transitions prior to 1994 and my sample changes to 1994-2019 for the job-to-job transitions.

3. Vacancies are measured as an index constructed based on the composite help-wanted index computed Barnichon (2010a), as it goes back to the beginning of my sample (1968).

4. Real GDP and wage (average hourly earnings) series are from BEA.

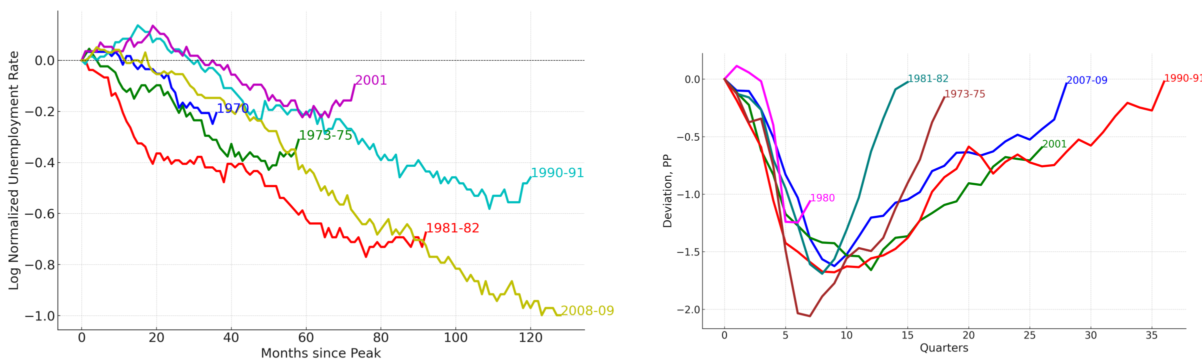
5. Aggregate productivity is measured as the Solow residual, for which I rely on the utility adjusted series from Fernald (2014), also updated by the Federal Reserve Bank of San Francisco.

6. Nowcast Errors: The GDP nowcast errors are constructed from the median forecast from the Survey of Professional Forecasters, which starts in 1968q4.

A.2 Recovery Pattern of the Labor Market

The labor market recovery has been sluggish and typically lags behind the recovery of output. Figure A1 illustrates the recovery pattern of unemployment and vacancies. In particular, the last three recessions before the pandemic have been slower. Specially the recessions occurring in 1990-91, 2001, and 2007-09, display distinct features from the postwar recoveries observed before the 1990s. In these recoveries, unemployment levels remained elevated, while both employment growth and job vacancies were sluggish for multiple quarters following the trough in output. I compute the duration to recover the rise in unemployment across various recessions. I calculate the following $u_{recovery}$ duration to recover 25%, 50%, 75% and 100% rise in unemployment across recessions. These are reported in Table 1.

Figure A1: Recoveries across Recessions



(a) Unemployment Rate

(b) Vacancies

Note: This figure plots the recovery of unemployment rate and vacancies from recessions to their pre-recession levels. The vacancy series is from Barnichon (2010a)

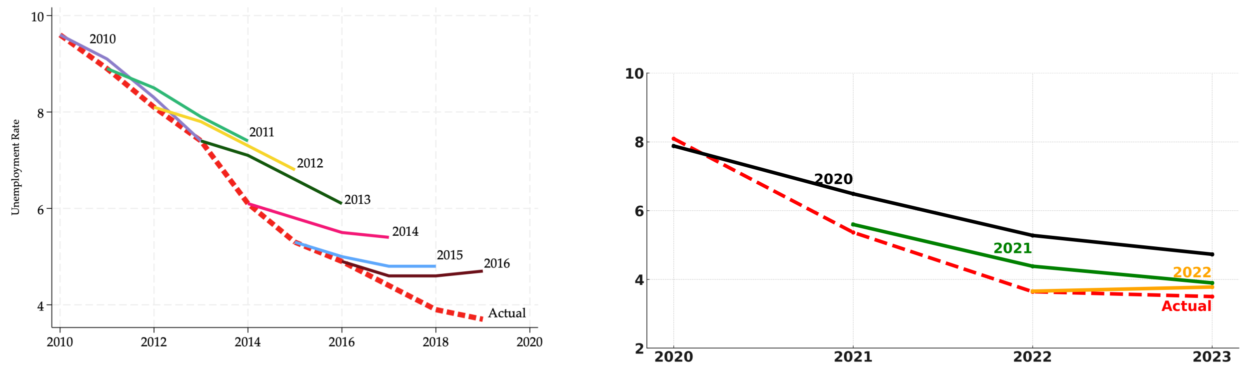
A.3 Projections from Forecasters and Policymakers

As noted in the introduction, the standard assumption in most macroeconomic model is that agents immediately recognize the nature of such a shock and adjust their expectations (and decisions). However, it can take agents much longer to learn about the true nature of the shock.

A.3.1 Professional Forecasters.

Survey of Professional Forecasters. To illustrate this point, I first present unemployment projections from the Survey of Professional Forecasters (SPF) during the recovery from the Great Recession in Figure A2. This illustrates that a) the forecasters consistently predicted unemployment to be higher than it actually was during the recovery from the Great Recession and, b) this misperception about the true nature of the shock likely contributed to higher persistence, as the historical decomposition of unemployment rate in Figure **??** suggests. The SPF documents long run projections starting in 2009 and hence long run projections are not available for earlier recessions.

Figure A2: Projected Unemployment Rate from Survey of Professional Forecasters:



(a) Projections: Great Recession

(b) Projections: Covid-19

Note: The various colored lines represents the median 1 year, 2 year and 3 year ahead projection of unemployment rate from the Survey of Professional Forecasters. The solid red line is the actual unemployment rate

However, I provide 1 year ahead forecasts in Figure A4a, which documents that forecasters almost always predict the recovery to be slower than it is.

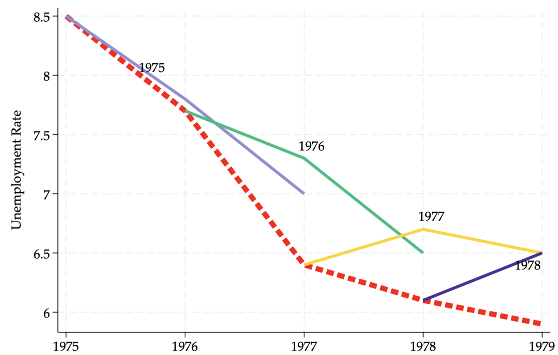
Livingston Survey The Livingston survey is the longest running survey of forecasters starting in 1946.[17] The survey is conducted twice a year and consists of forecasts of 18 different variables describing unemployment, output, prices, and other macroeconomic data. The forecasts are by economists from industry, government, banking, and academia.

Figure A3 depicts the 1 year and 2 year ahead median forecasts by the forecasters in the Livingston survey for the 1973-74 recession in the left panel and the 2007-09 recession in the right panel. Qualitatively the results are similar to what the SPF forecasters expected. Across recessions, forecasters over estimated the recovery of unemployment rate. This re-enforces the idea that agents cannot distinguish between a persistent and transitory shock immediately and may take several quarters to learn.

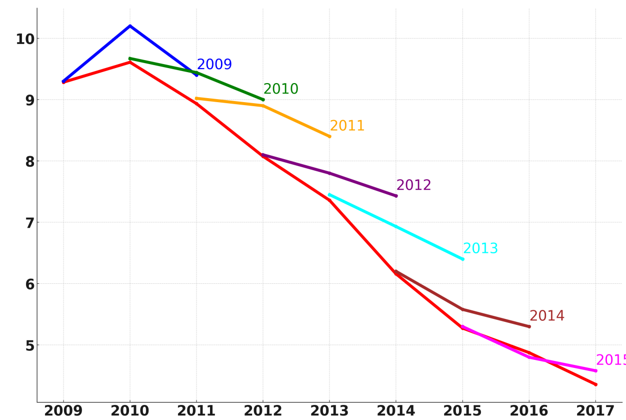
Policymakers. Now, to illustrate that it can be challenging even for policymakers to correctly assess the nature of the recession, I present the projections from Federal Reserve's Greenbook in December 2008 in Figure A4b. Under all scenarios, the Federal Reserve Board predicted a much faster recovery during the Great Recession.

[17]It is publicly available and is fielded by the Federal Reserve Bank of Philadelphia who took over from Joseph Livingston.

Figure A3: Projected Unemployment Rate from the Livingston Survey



(a) 1973-74 Recession



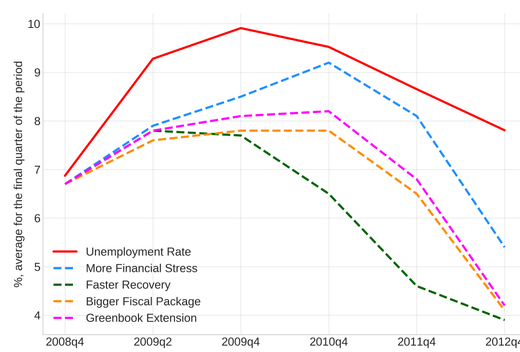
(b) 2009-07 Recession

Note: The various colored lines represents the median 1 and 2 year ahead projection of unemployment rate from the Livingston Survey. The solid red line is the actual unemployment rate

Figure A4: Projected Unemployment Rate from the SPF

(a) 1 year ahead Unemployment Forecast from Survey of Professional Forecasters

(b) Projected Unemployment Rate: Fed. Greenbook, December 2008



Note: Panel (a): The black dashed line represents the median 1 year ahead projection of unemployment rate from the Survey of Professional Forecasters. The solid red line is the actual unemployment rate. Panel (b): The black dashed line represents the projection of unemployment rate from the December 2008 Greenbook released by the Federal Reserve Board. The dashed lines represent projections under various scenarios that the Fed simulated. The solid red line is the actual unemployment rate.

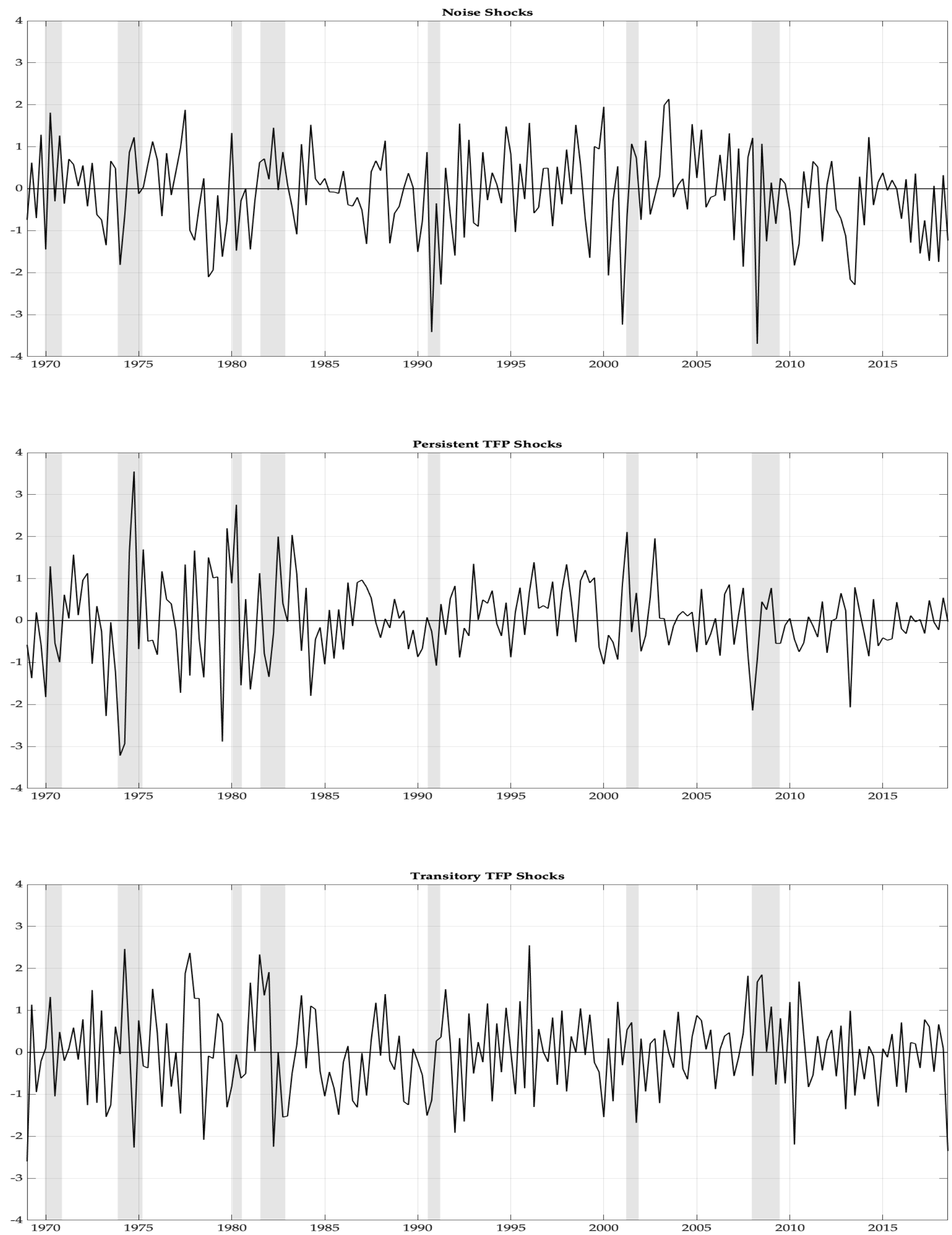
A.4 SVAR

In this section I discuss some more results and robustness from the SVAR. First, I present the shock series identified from the VAR in Figure A5.

VAR Impulse Response Functions. The VAR's impulse responses, illustrated in Figure A6, align with both the model's stipulated assumptions and economic reasoning. Specifically:

1. Noise Shocks: These do not affect TFP but instantly reduce nowcast errors while boosting

Figure A5: Shock Series



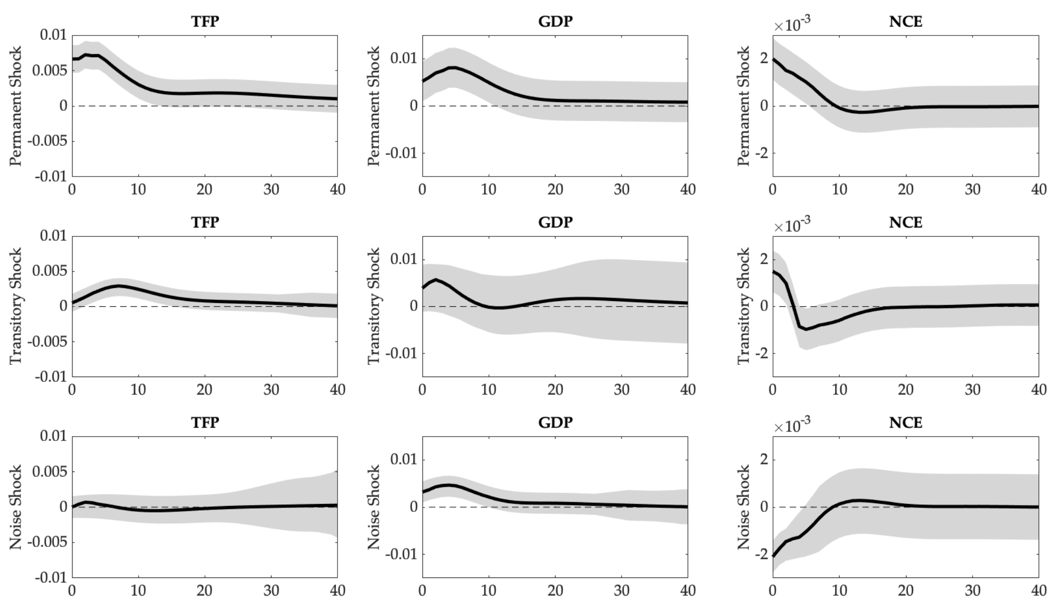
Note: This figure plots the time series of noise shocks, persistent TFP shocks, and transitory TFP shocks, as identified in the SVAR. The persistent TFP shocks have lower volatility post 1985 while the noise shocks have higher volatility.

GDP. These are imposed by the VAR on impact. However, we see in the dynamics that the nowcast errors remain negative for about 8 quarters which implies that the agents keep getting surprised as they expect GDP to be higher than it is. This suggests that they do not immediately recognize the shock as noise and attribute it to a persistent or transitory change in productivity. This is once again consistent with learning under imperfect information.

2. Persistent Shocks: These raise TFP in a manner that aligns with a long-lasting shock. Concurrently, GDP and nowcast errors increase immediately. Even after several quarters, nowcast errors stay elevated, indicating that these persistent shocks continually surprise economic agents and they misperceive the shocks.

3. Transitory Shocks: These momentarily elevate both TFP and output, but their effect is short-lived. Initially, nowcast errors rise due to these shocks but soon turn negative. This indicates that agents mistakenly view the shock as persistent for a duration and continue to be surprised since it's actually a tranbsitory shock with minimal long-term effects on productivity and GDP.

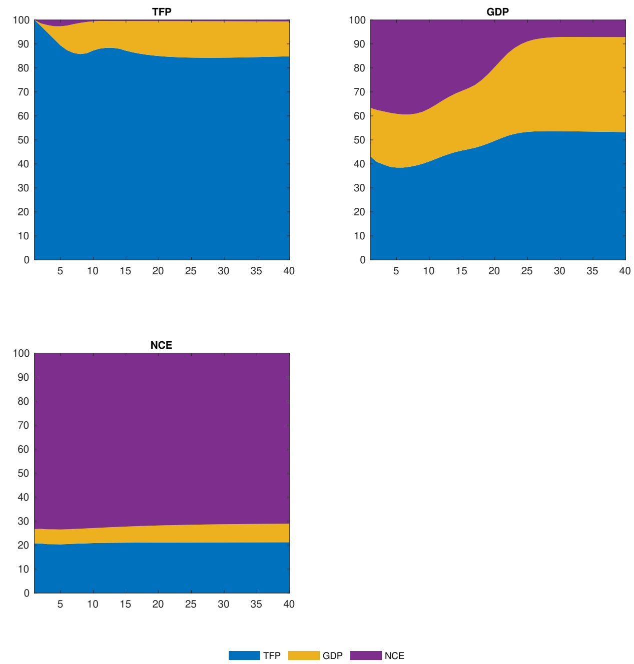
Figure A6: Impulse Response from the VAR



Note: This figure plots the impulse response functions for the variables in the VAR to a persistent shock, a transitory shock and a noise shock, identified using the SVAR described by the optimization problem in 7. The sample period is 1968q4: 2019q4.

The figure A7 plots the forecast error variance contribution of each shock to TFP, GDP and the nowcast errors (NCE). The blue shaded area is attributed to the persistent shock, the yellow is attributed to the transitory shock and the purple is attributed to the noise shocks. As expected, the maximum forecast error variance of TFP is explained by the persistent shock. We also see that the noise shock does not contribute significantly to the forecast error variance of TFP, which is consistent with the assumptions of the VAR. The nowcast errors are mostly explained by the noise shocks while GDP is intitally explained to a large extent by the noise shocks but as the horizon increases, persistent shock becomes the primary driver of forecast error variance of GDP. This is also in line with economic intutition – as noise shocks die down, GDP is explained by the actual TFP shocks in the long run.

Figure A7: FEVD after Max-Share Identification



Note: This figure plots the forecast error variance decomposition for TFP, GDP and the Nowcast errors (NCE). The blue shaded area is attributed to the persistent shock, the yellow is attributed to the transitory shock and the purple is attributed to the noise shocks.

A.5 Smooth Linear Projections

In this section, I describe the method used to estimate the SLP, following Barnichon and Brownlees (2019). They model the sequence of impulse response coefficients as a linear combination of B-splines basis functions. These are estimated using a shrinkage estimator that shrinks the impulse response toward a polynomial. SLP coincides with LP when the degree of shrinkage is low and with polynomial distributed lag model with a high degree of shrinkage. Consider a LP of the form:

$$y_{t+h} = \alpha_h^j + \beta_h^j u_t^j + \sum_{p=1}^{P} \gamma_p^j \omega_{t-p} + \mu_{h,t+h}^j \tag{39}$$

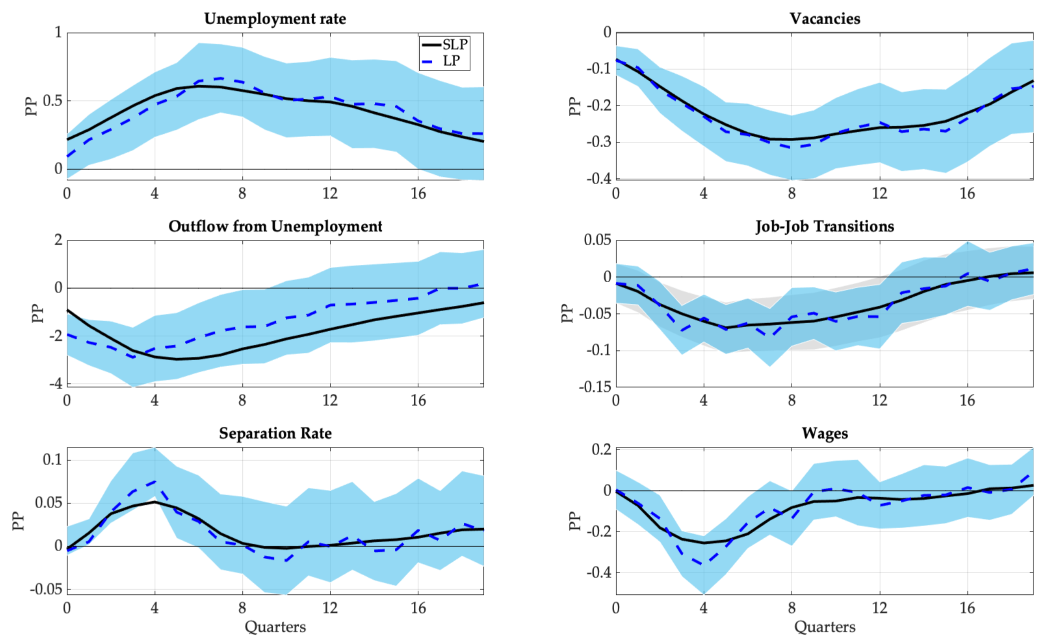
where ω_{t-p}^j is the set of lagged values of y and u^j.

Following Barnichon and Brownlees (2019), one can approximate $\beta_h^j \approx \sum_{k=1}^{K} b_k^j B_k^j(h)$ using a linear B-splines basis function expansion in the forecast horizon h. Thus, the corresponding smooth Linear Projections can be written as Equation 40.

$$y_{t+h} \approx \sum_{k=1}^{K} a_k^j B_k(h)^j + \sum_{k=1}^{K} b_k^j B_k^j(h) u_t^j + \sum_{p=1}^{P}\sum_{k=1}^{K} c_{pk}^j B_k^j(h)\omega_{t-p}^j + \mu_{h,t+h}^j \tag{40}$$

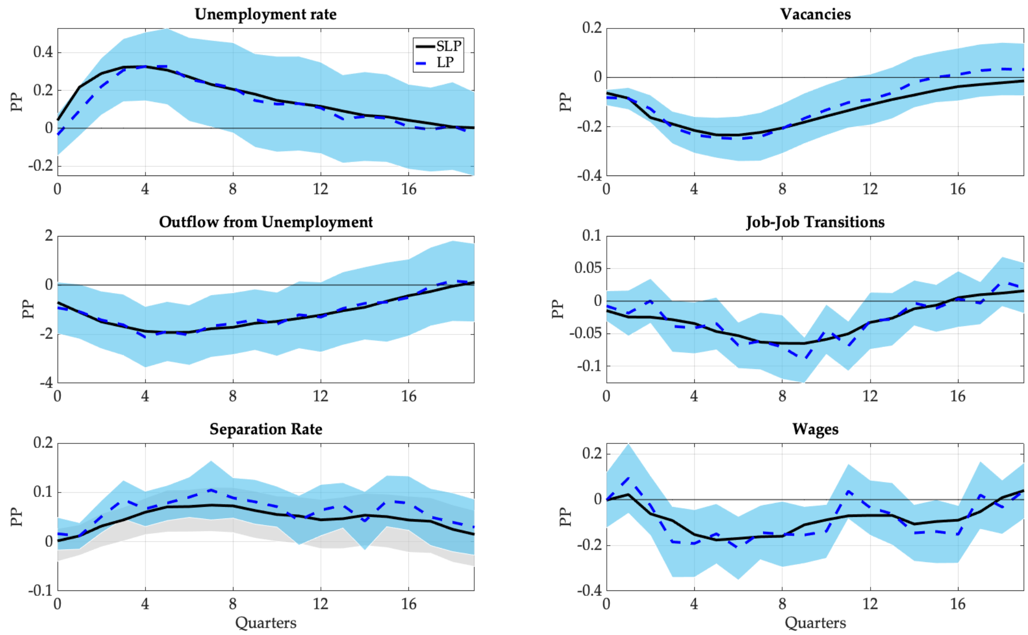
The SLP is estimated using generalized ridge estimation. When the shrinkage parameter is small, it is close to the least square estimation and has zero bias but potentially large variance.When the shrinkage parameter is large, the estimator is biased but has smaller variance than the least squares estimator. The shrinkage parameter is chosen using k-fold cross-validation (Racine (1997)). I present the impulse responses from the local projection and their smoothed counterparts for the noise shock in Figure A9 and the persistent shock in Figure A8. The IRFs from the smoothed LPs are qualitatively and quantitatively similar to the local projections.

Figure A8: Smoothed Impulse Response to Persistent TFP Shocks



Note: This figure plots the impulse responses from the local projection and their smoothed counterparts for the persistent TFP shock. The shaded area represents a 95% confidence interval for the local projection.

Figure A9: Smoothed Impulse Response to Noise Shocks



Note: This figure plots the impulse responses from the local projection and their smoothed counterparts for the noise shock. The shaded area represents a 95% confidence interval for the local projection.

A.6 Empirical Results

A.6.1 Impulse Response to Transitory TFP Shock

Figure A10 illustrates the response of labor market variables to a transitory TFP shock. The response to a transitory shock is muted and is less than that of noise shocks in terms of magnitude.

A.6.2 Historical Decomposition

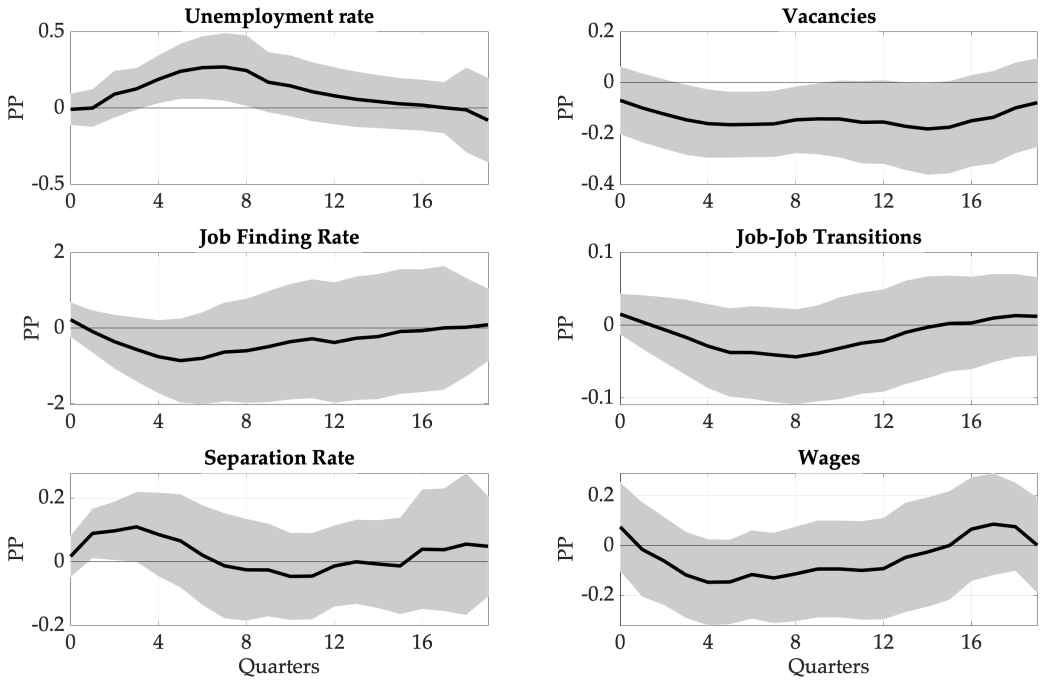
To understand the role of imperfect information over the business cycle, it is useful to understand how much of the deviation of the key labor market outcomes from their predicted path can be explained by the productivity shocks. If noise shocks are not important, the productivity shocks would explain almost all the fluctuations in these variables. The VAR model in its Vector Moving Average form is

$$y_t = e_t + \Psi_1 u_{t-1} + \ldots + \Psi_t u_1 + \bar{\Psi}_t \quad (41)$$

$$= \psi_0 v_t + \psi_1 v_{t-1} + \ldots + \psi_t v_1 + \bar{\Psi}_t \quad (42)$$

where, $\psi_0 = Q$ and $\psi_j = \Psi_j Q$ are functions of $A_1, \ldots, A_p$ and Q. $\bar{\Psi}_t$ is the pure deterministic

Figure A10: Impulse Response to Transitory TFP Shocks



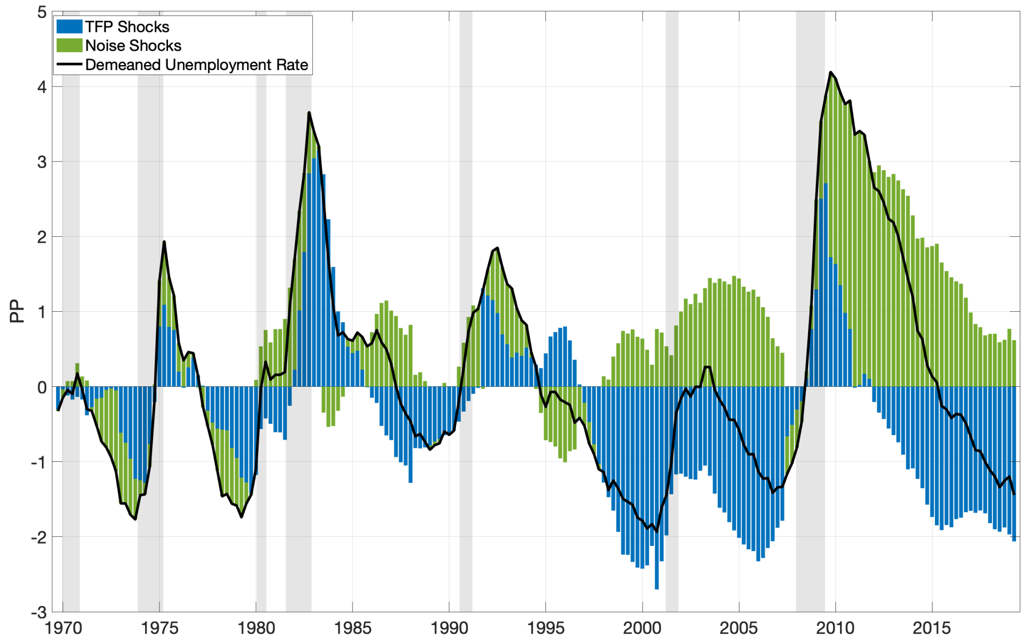
Note: This figure plots the impulse response functions for key labor market variables to a transitory TFP shock. The shaded area represents a 95% confidence interval.

component. Now, we can decompose $(y_t - \bar{\Psi}_t)$ as the sum of the contribution of n shocks

$$y_t - \bar{\Psi}_t = \sum_{j=0}^{t} \psi_j v_{t-j}^1 + \ldots + \sum_{j=0}^{t} \psi_j v_{t-j}^n \tag{43}$$

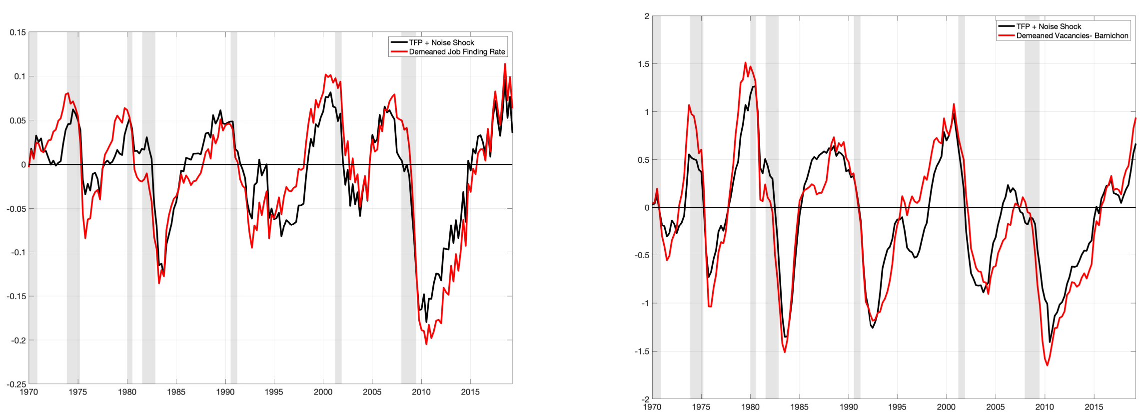
In Figure A11, I present the contribution of the two TFP shocks (in blue) and the noise shocks (in green) in the VAR to the movements in unemployment rate. The noise shocks contribute significantly to the unemployment rate during the recessions in 1990-91, 2001 and 2007-09. In Figure A12 I plot the cumulative contribution of the TFP shocks and noise shocks to the outflow from unemployment as well as the vacancy postings. These three shocks explain almost all the movement in the outflow from unemployment and vacancy postings across the business cycle. When combined with Figure 5b and Figure 5c, these graphs establish that the noise shocks play an important role in driving the dynamics of key labor market outcomes specially post 1985, as the TFP shocks do not fully explain the fluctuations while the noise shocks contribute substantially to these movements.

Figure A11: Historical Contribution of Shocks to Unemployment Rate



Note: This figure plots the historical decomposition of unemployment rate following equation 16. The blue bars are the cumulative contribution of the identified persistent and transitory TFP shocks to the movements in demeaned unemployment rate (black line). The green bars are the contribution of the noise shocks.

Figure A12: Historical Contribution of Persistent, Transitory and Noise Shocks

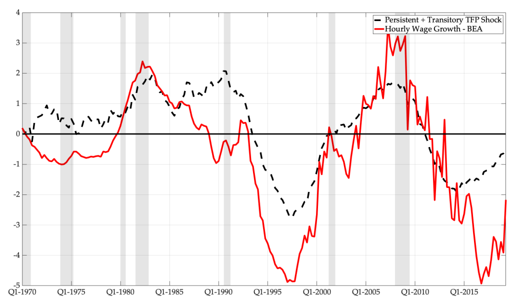


(a) Job Finding Rate

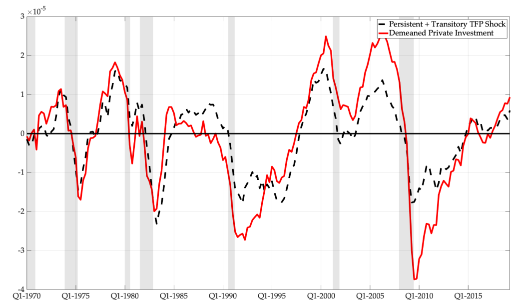
(b) Vacancy Posting

Note: This figure plots the historical decomposition for each series following equation 16. The black line is the cumulative contribution of the identified persistent, transitory and noise shocks to the movements in demeaned unemployment rate (red line).

Figure A13: Historical Contribution of Persistent, Transitory and Noise Shocks



(a) Wage Growth



(b) Private Investment

Note: This figure plots the historical decomposition for each series following equation 16. For wage growth, he black line is the cumulative contribution of the identified persistent, transitory and noise shocks to the movements in demeaned unemployment rate (red line). For private investment, the blue bars are the cumulative contribution of the identified persistent and transitory TFP shocks to the movements in demeaned unemployment rate (red line). The green bars are the contribution of the noise shocks.

A.6.3 Persistence of Unemployment

To understand the contribution of the noise shocks to the persistence of unemployment, I compute for each recession between 1968-2019, the share of the rise in unemployment during the recession that has been reversed during the expansion. I then define persistence as the number of quarters to recover 50% of the rise in unemployment during a recession, that is $u_{recovery,t} = 0.5$. Now, from the historical decomposition, I can calculate what fraction of this persistence can be attributed to each of the shock by first computing the predicted unemployment rate from each shock and then calculating the persistence as defined above. The results are summarized in Table A1. For the great recession, noise shocks account for about 35% of the 50% of the rise in unemployment and on average noise shocks account for 27% of this recovery across recessions.

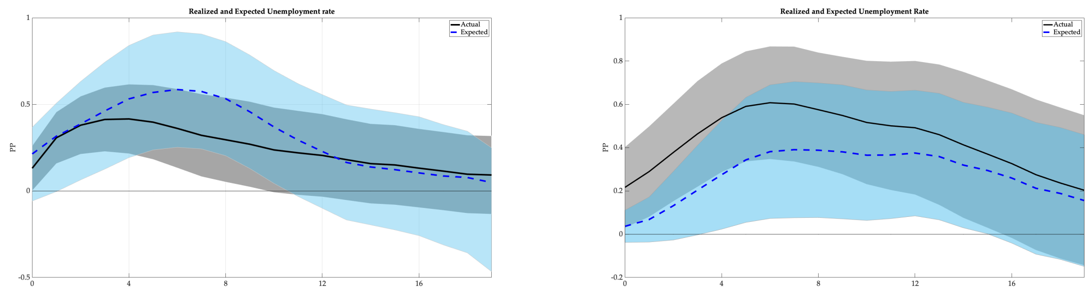
Table A1: Contribution of Noise Shocks to Recovery of Unemployment Across Recessions

	No of quarters for 50% recovery	
Recession	Data	Share explained by Noise shocks
2007-09	20	35%
2001	15	33%
1990-91	18	28%
1981-82	18	33%
1973-75	17	29%
Average	17.6	32%

Note: This table reports the number of quarters to recover 50% of the rise in unemployment during a recession, that is $u_{recovery,t} = 0.5$.

A.6.4 Response of Unemployment Forecast Errors

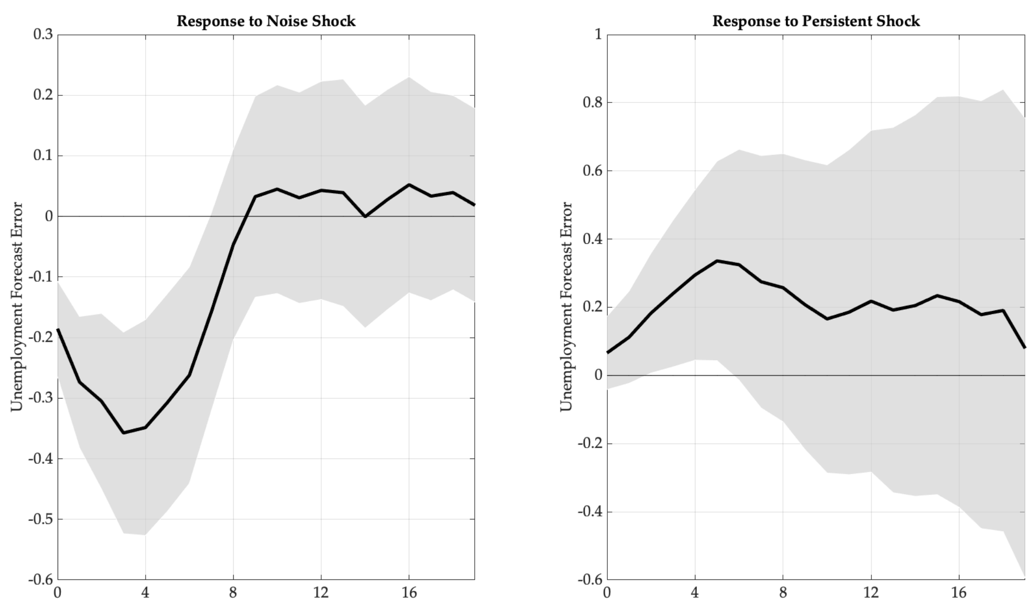
Figure A14: Unemployment Rate: Projections and Actual



(a) Unemployment Projections: Noise Shocks (b) Unemployment Projections: Persistent Shock

Note: Panel (a) shows the response of actual unemployment rate (solid, black) and expected unemployment rate from the SPF (dashed,blue) to a one standard deviation noise shock, for the duration 1968-2019. Panel (b) shows the response of actual unemployment rate (solid, black) and expected unemployment rate from the SPF (dashed,blue) to a one standard deviation persistent TFP shock, for the duration 1968-2019.

Figure A15: Response of Unemployment Forecast Error to Shocks



Note: This figure plots the response of unemployment forecast error from the SPF for 1968-2019 to Noise Shocks in Panel(a) and to Persistent TFP Shocks in Panel (b).

A.6.5 Sub-Sample Analysis

In this subsection, I discuss a sub-sample analysis to address investigate whether there were structural changes in the business cycle post the Great Moderation in 1985. I first present some simple statistics from the SVAR identified shocks as well as the nowcast errors in Table A2. I find that post 1990, the noise shock became more volatile while the persistent shocks have become less volatile. Interestingly, the unemployment nowcast errors not only became more volatile, but also the average flipped sign post 1990 implying that forecasters on an average, predict unemployment to be higher than it is in this period. Likewise for output growth, forecasters predict output to be lower than it is. This suggests some structural change that might have happened post Great Moderation, and I leave it for future work to investigate it's source.

Table A2: Summary Statistics Pre and Post 1990

	1968-1989		1990-2019	
	Mean	SD	Mean	SD
Unemployment Rate	5.68	1.65	5.80	1.83
GDP Nowcast Error	0.06	1.72	0.25	2.59
Unemployment Nowcast Error	0.07	0.695	-0.03	1.20
Noise Shock	0.04	0.745	-0.05	1.27
Persistent Shock	-0.21	1.34	0.03	0.68
Transitory Shock	0.18	0.83	0.27	0.89

Note: This table reports summary statistics from 1968-1989 and 1989-2019 in the empirical exercise.

A.7 Robustness: Controlling for Uncertainty Shocks.

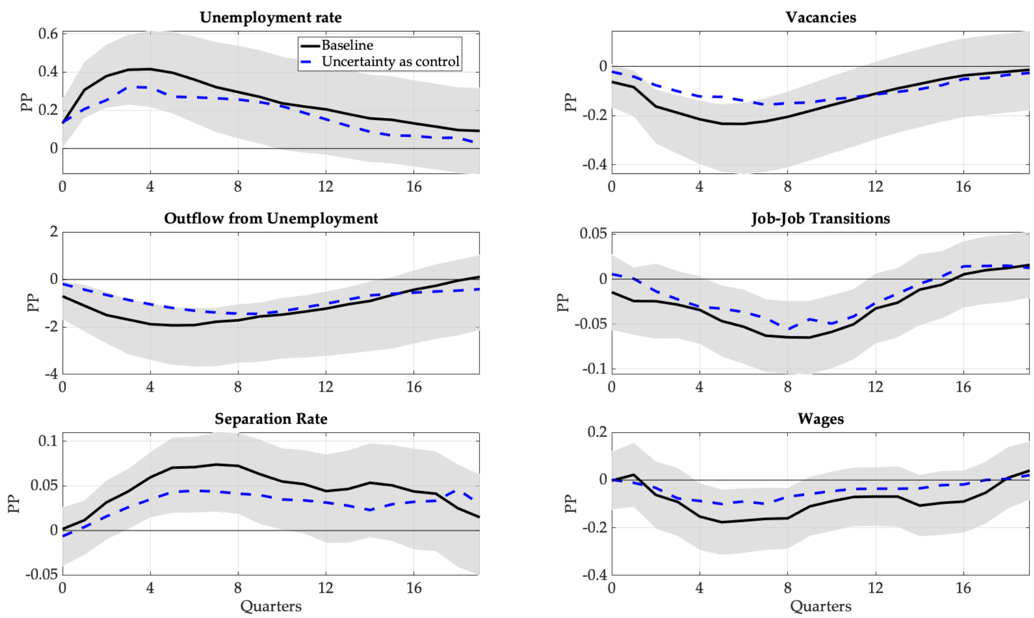
Fundamental shocks do not satisfy the sign restrictions used to identify the noise shocks, as any fundamental shock has a higher impact on actual output than expected, thus violating the sign restrictions. However, there might be some cases where uncertainty shocks might behave like the noise shocks: generate a larger change in expected output than actual output. To address this concern, I control for the uncertainty shock series from Bloom (2009) in the linear projections. This robustness is to test whether the noise shocks are independent of uncertainty shocks. If the noise shock was indeed capturing uncertainty shocks, controlling for uncertainty shock would then capture the response otherwise attributed to the noise shock. I specifically estimate the regression in Equation 44.

$$y_{t+h} = \alpha_h + \tilde{\beta}_h u_t^{noise} + \theta_h u_t^{uncertainty} + \sum_{p=1}^{P} \tilde{\gamma}_p \tilde{\omega}_{t-p} + \tilde{\mu}^j_{h,t+h} \tag{44}$$

where $\tilde{\omega}^j_{t-p}$ is the set of lagged values of y, u^{noise} and $u^{uncertainty}$. I then plot the respective smoothed cumulative impulse response to the noise shock ($\tilde{\beta}$). The baseline is Equation 39 where I compute the smooth cumulative impulse response to a noise shock without controlling for uncertainty shock.

The results of this exercise are shown in Figure A16. This exercise shows that controlling for uncertainty shocks does not change the response of key labor market outcomes to a standardized negative noise shock. The impulse responses for all the outcomes in the labor market lie within the 90 percent confidence interval of the baseline impulse responses. Furthermore, the hump-shape of the responses are retained, which are consistent with Bayesian learning. This exercise suggests that the noise shocks are not capturing the uncertainty shocks.

Figure A16: Impulse Response to a Noise Shock When Controlling for Uncertainty



Note: This figure plots the impulse response of key labor market outcomes to the noise shocks with and without controlling for uncertainty shocks. The solid black line is the smoothed cumulative coefficient β from Equation 39. The blue dashed line is the smoothed cumulative coefficient $\tilde{\beta}$ from Equation 44. The impulse responses are smoothed by following Equation 40 respectively. The error bands plot the 90 percent confidence interval.

B Theoretical Appendix

In this section I derive some theoretical results and discuss various mechanisms in detail. I conduct some sensitivity analysis with alternate calibrations that are documented in this section.

B.1 Information Structure

Consider the following state-space representation:

$$\begin{aligned}
z_t &= x_t + \eta_t, & \eta_t &\sim \text{iid } N(0, \sigma_\eta^2) \\
x_t &= \rho_x x_{t-1} + \epsilon_t, & \epsilon_t &\sim \text{iid } N(0, \sigma_\epsilon^2) \\
a_t &= x_t + n_t, & & \\
n_t &= \rho_n n_{t-1} + \nu_t, & \nu_t &\sim \text{iid } N(0, \sigma_\nu^2)
\end{aligned}$$

Where:

- z_t is the observed sum.
- a_t is the observed public signal.
- x_t is the underlying state variable.

Kalman Gain Derivation The Kalman gain is derived from the following general equation:

$$K_t = P_{t|t-1} H' (H P_{t|t-1} H' + R)^{-1} \tag{45}$$

Given the system, the state transition matrix F:

$$F = \begin{bmatrix} \rho_x & 0 \\ 0 & \rho_n \end{bmatrix} \tag{46}$$

Observation matrix H:

$$H = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \tag{47}$$

Process noise covariance matrix Q:

$$Q = \begin{bmatrix} \sigma_\epsilon^2 & 0 \\ 0 & \sigma_\nu^2 \end{bmatrix} \tag{48}$$

Measurement noise covariance matrix R:

$$R = \begin{bmatrix} \sigma_\eta^2 & 0 \\ 0 & 0 \end{bmatrix} \tag{49}$$

Using these matrices, the Kalman gain is:

$$K_t = P_{t|t-1} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \left(\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} P_{t|t-1} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} \sigma_\eta^2 & 0 \\ 0 & 0 \end{bmatrix} \right)^{-1} \tag{50}$$

In steady-state, the error covariance matrix does not change over time, i.e., $P_{t+1|t} = P_{t|t-1} = \bar{P}$. The steady-state Riccati equation is:

$$\bar{P} = F\bar{P}F^T + Q - F\bar{P}H^T(H\bar{P}H^T + R)^{-1}H\bar{P}F^T \tag{51}$$

From this equation, the variance of the estimation error for x_t in steady-state is given by $\bar{P}_{11}$. Given the structure of the processes, the Kalman gain matrix is given by

$$\mathbf{K}_t = \left[\frac{\frac{1}{\sigma_z^2}}{\frac{1}{\sigma_z^2} + \frac{1}{\sigma_{x,t}^2} + \frac{1}{\sigma_s^2}} ; \frac{\frac{1}{\sigma_s^2}}{\frac{1}{\sigma_z^2} + \frac{1}{\sigma_{x,t}^2} + \frac{1}{\sigma_s^2}} \right] \tag{52}$$

where, $\sigma_{x,t}^2$ is the conditional forecast variance of $x_{t+1} \equiv Var_t(x_{t+1})$. It is updated according to the standard Riccatti equation:

$$\sigma_{x,t}^2 = \rho_x^2 \left(\frac{1}{\sigma_s^2} + \frac{1}{\sigma_z^2} + \frac{1}{\sigma_{x,t-1}^2} \right)^{-1} + \sigma_x^2 \tag{53}$$

where,

$$\sigma_z^2 = \mathrm{Var}(z_t) = \sigma_x^2 + \sigma_\eta^2 \tag{54}$$

$$= \frac{\sigma_\epsilon^2}{1-\rho_z^2} + \sigma_\eta^2 \tag{55}$$

$$\sigma_s^2 = \mathrm{Var}(\hat{s}_t) = \sigma_x^2 + \sigma_a^2 \tag{56}$$

$$= \frac{\sigma_\epsilon^2}{1-\rho_z^2} + \frac{\sigma_\nu^2}{1-\rho_a^2} \tag{57}$$

B.2 Estimation: Full Information

In this section I present the results for re-calibration of the full information model to match the impulse responses from the persistent TFP shocks.

Table B1: Estimated Parameters from IRF Matching: Full Information Model

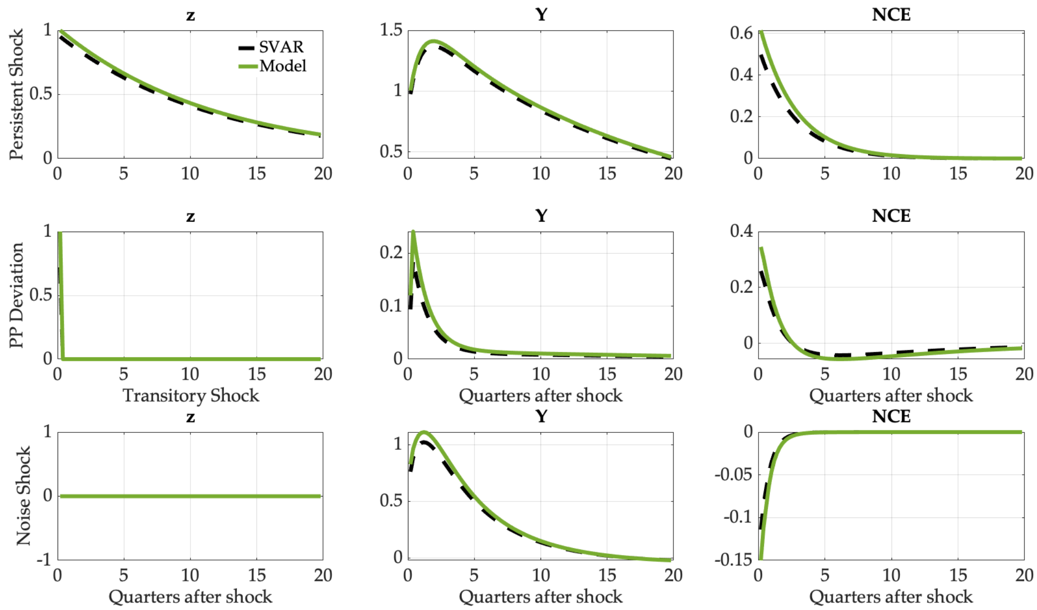
Parameters	Interpretation	Value	Target
Ψ	Match efficiency	0.48	Unemployment Rate = 0.055
κ	Cost of hiring	8.23	$U-E$ = 0.28
μ	Scale parameter of search cost	0.082	$E-E$ = 0.025
$1-\sigma$	Separation rate	0.010	$E-U$ = 0.010
ϕ	SS productivity from bad job	0.68	Δ Wage of E-E = 0.045
Parameters	**Interpretation**	**Estimate**	**Std. Error**
λ	Renegotiation frequency	0.88	0.13
ξ	Probability of finding a good job	0.18	0.05
η_h	Hiring cost convexity	0.34	0.09

Note: This table reports the estimated parameters from the impulse response matching exercise outlined in equation 38 for the Full information model. The third column reports the estimated values while the fourth column reports the standard errors for these values. The impulse responses are matched by GMM and the standard errors are calculated using the delta method.

B.3 Internal Validity of the SVAR

In this section, I describe the internal validity of the SVAR. To do this, I first simulate the estimated model for 10,000 periods. Then, I use this model model generated data in the SVAR to identify the three shocks. The test of the SVAR is that if the identification strategy indeed recovers the true shocks, then for a large sample, the model generated impulse response must be equivalent to the impulse responses generated by the SVAR implemented on the simulated data. These impulse response functions are presented in Figure B1, where these two IRFs coincide. This implies that the identification strategy indeed recovers the true shocks in the model.

Figure B1: Internal Validity of the VAR



Note: This figure plots the internal validity for the SVAR in the estimated model with imperfect information. The dashed black lines are the simulated data implied IRFs in the SVAR (p = 8, T = 10,000), whereas the solid green lines are the model implied IRFs.

B.4 Quantitative Results

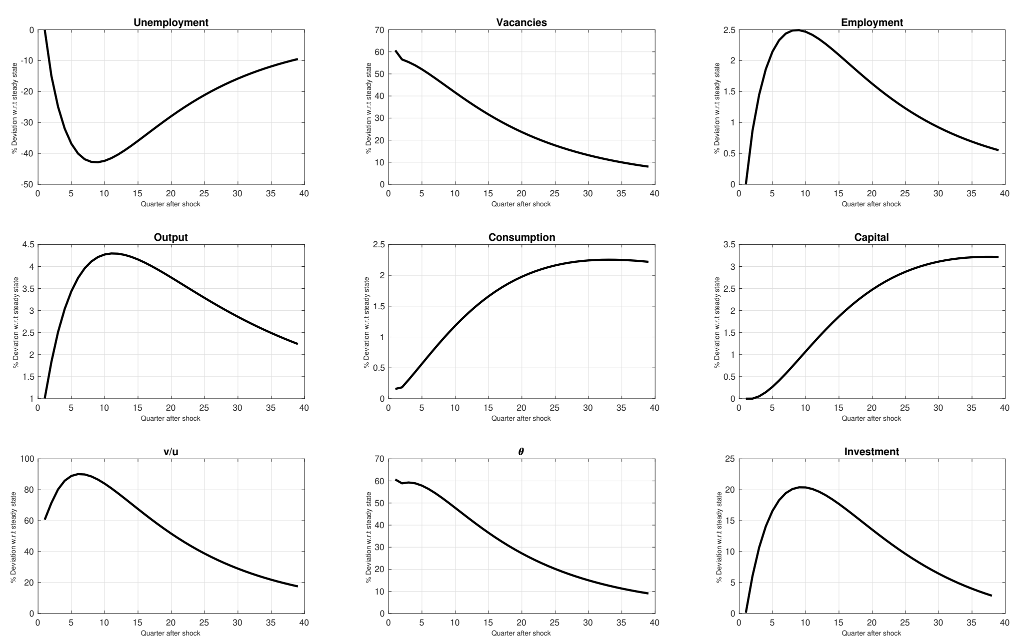
B.4.1 Impulse Responses From the Model

Here I plot impulse response functions from the imperfect information sticky wage with on-the-job search model for other important outcomes like output, investment.

Figure B2: Model Implied Impulse Response Functions to a Negative Noise shock

Note: This figure plots the model implied, impulse response functions to a noise shock.

Figure B3: Model Implied Impulse Response Functions to a Positive Persistent Productivity

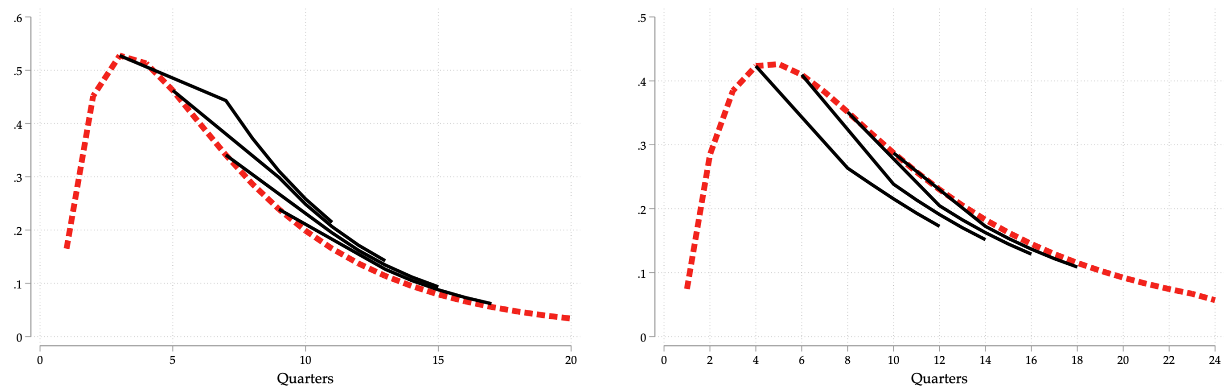


Note: This figure plots the model implied, impulse response functions to a persistent productivity shock.

B.5 Projections from the Model

In this section, I present the 4-8 quarters ahead projections by the agents in the model in response to a persistent TFP shock and in response to a noise shock. When faced with a persistent TFP shock, due to imperfect information, agents attribute a part of the shock to be noise as well as transitory shock and hence their projections under-react to the actual unemployment rate. However, the reverse happens when they face a noise shock. They similarly attribute some part of the shock to be persistent or transitory productivity and hence initially expect unemployment to be higher than it actually is (since true productivity has not changed). They eventually start placing more and more weight on the shock being noise and as they learn, their projections are closer to the actual.

Figure B4: 4-8 Quarter Ahead Projections in the Model

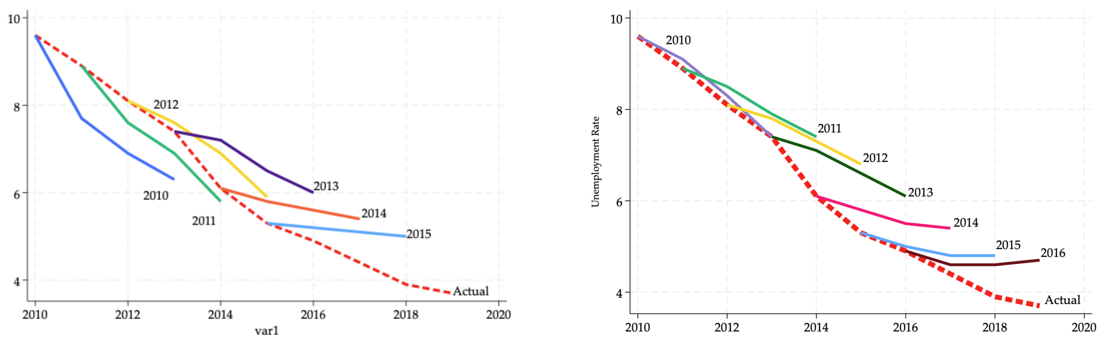


(a) Noise Shock (b) Persistent Productivity Shock

Note: This figure shows the 4-8 quarters ahead projections by the agents in the model in response to a response to a noise shock (a) and a persistent TFP shock (b). The solid thick black line is the actual response of unemployment due to these shocks respectively.

Figure B5a shows the model generated, one, two and three year ahead unemployment projections in the model after the Great Recession. Here, all three shocks, identified from the VAR, act together each period while simulation the imperfect information model with noise shocks. Since all three shocks act, the projections under-react if the contribution of the persistent shock dominates the contribution of the noise shocks as well as transitory shocks. Similarly, as the contribution of the noise shocks dominates, the projections over-estimate the unemployment rate. As seen in the historical decomposition of the unemployment rate in the data in Figure A11, the contribution of the noise shocks to the movement in unemployment dominates after 2012. Thus, in the model, initially, as the productivity shocks have higher weight, the unemployment rate is under-estimated by the agents in the model. However, from 2012, the contribution of the noise shocks increases but the agents are unable to discern the shock from a true persistent productivity shock and hence keep expecting higher unemployment rates in the future. However, as the shock is truly noise, the actual unemployment rate is lower than expected. This is similar to the pattern seen in the data in Figure B5b. It is important to note that the noise shocks are unique in generating over-estimation of long run unemployment projections. For all structural shocks, the long run expectations underestimate the unemployment rate. Thus, noise shocks can be a potential solution to the consistent pattern observed in the data where the long-run unemployment forecasts are over-estimated by professional forecasters.

Figure B5: Unemployment Rate: Projections and Actual– Model vs Data



(a) Unemployment Projections: Model

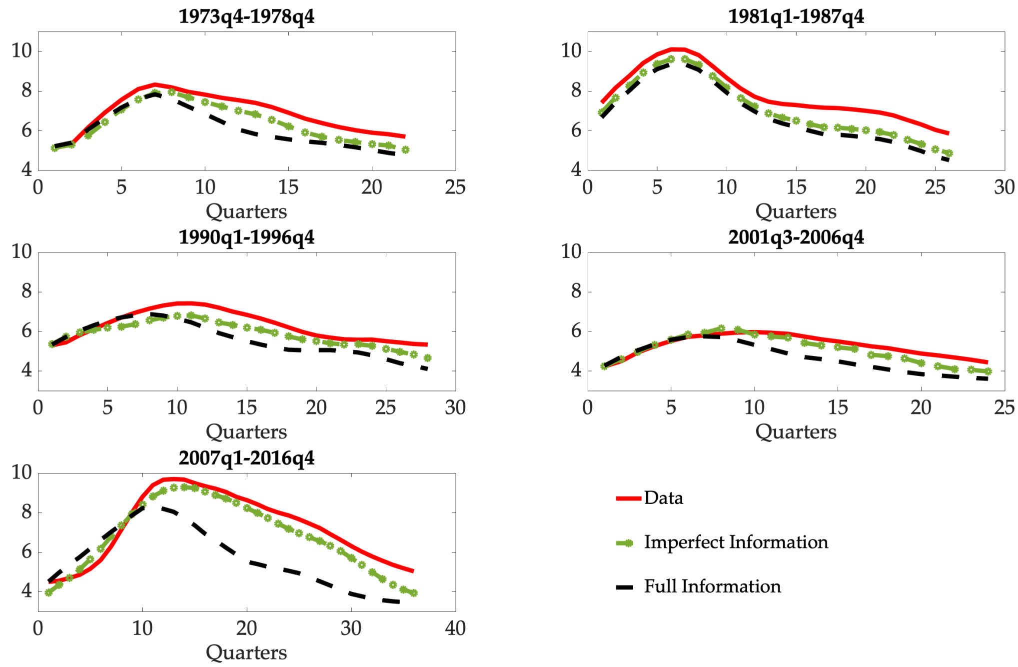
(b) Unemployment Projections: Data

Note: Panel (a) shows the model implied forecasts for unemployment rate 1,2 and 3 years ahead. The dashed black line is the model simulated unemployment rate for the Great Recession. While simulating the model, each period all three shocks act. In Panel (b) the various colored lines represent the median long-run (1 year, 2 year and 3 year ahead) projections of the unemployment rate from the Survey of Professional Forecasters during the Great Recession. The dashed red line is the actual unemployment rate.

B.5.1 Unemployment Dynamics across Recessions: Data vs Model

The calibrated model is simulated to generate counterfactual unemployment rate series for 5 recessions between 1970-2019. This exercise shows that imperfect information explains the slow recovery of unemployment rate in the last three recessions. For this exercise, the model is normalized to match the starting unemployment rate for each of the recessions. While simulating the imperfect information model, each period, all three identified shocks from the VAR are incorporated. For the full information model, I only introduce the persistent and the transitory shocks each period. Furthermore, the full information model is re-estimated as described in the previous section, to match the empirical IRFs to the persistent TFP shocks. The estimated parameters for the full information model is presented in the Appendix.

Figure B6: Model Implied Recovery of Unemployment for Recessions



Note: This figure plots the model implied, simulated unemployment rate for the re-calibrated full information model (dashed blue line) and the imperfect information model (solid green line) for major recessions between 1973-2019.

B.5.2 Comparing Mechanisms in the Model

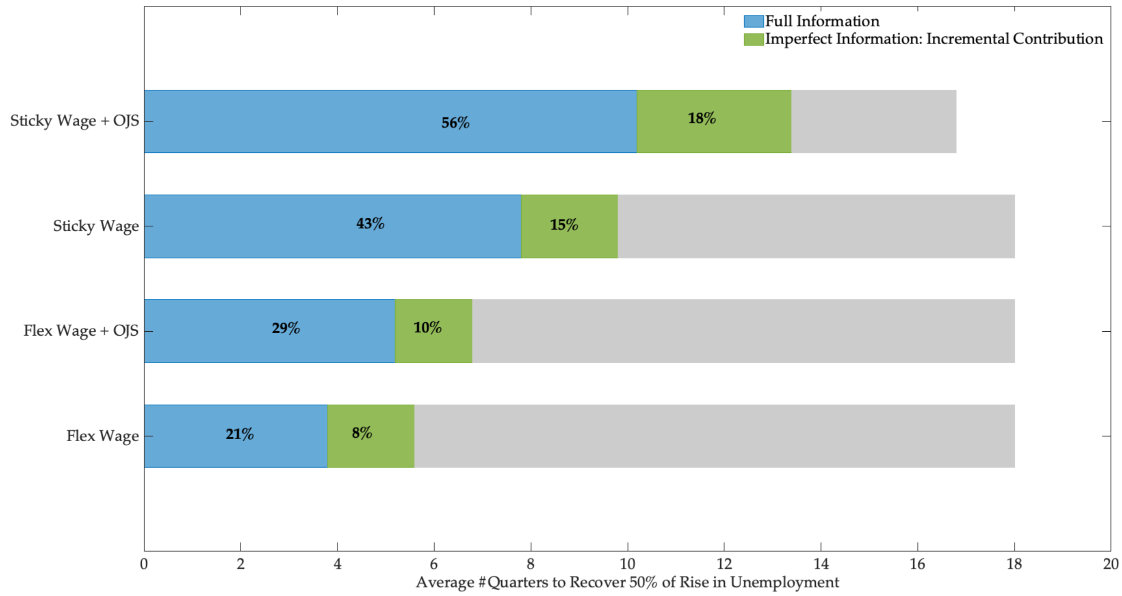
In this section, I compare the persistence and volatility of unemployment under various mechanisms with and without imperfect information. I compare the model under 4 scenarios: a) flexible wages without on-the-job search (OJS), b) flexible wages with OJS, c) sticky wages without OJS, and d) sticky wages with OJS.

Persistence To capture the persistence of unemployment, I compare the average duration to recover the 50% of the rise in unemployment across recessions between 1968-2019. Figure B7 shows the decomposition for the four difference model specifications, and within each specification I further decompose the re-calibrated full information benchmark to the imperfect information model without noise.

The main takeaway of this graph is that introducing learning endogenously contributes to persistence in unemployment rate in the model. This speaks to Wright (1986), who finds that imperfect information (albeit about wages, and on worker side), introduces learning endogenously in presence of job search.

I also present the full duration of recovery across recessions in the Table B2 for the re-estimated full information model and the imperfect information model. This measure captures the duration of recovery by calculating the number of quarters it took the unemployment rate to return to it's

Figure B7: Average Duration to Recover 50% of Rise in Unemployment Across Models



Note: This figure plots the model implied duration from the beginning of the recessions to recover 50% of the rise in unemployment. This is averaged across the recessions between 1968-2019, for various model specification. The percentages are the percent of the data (18 quarters) that the particular model specification explains, while the x-axis is the actual number of quarters explained by the particular specification. The green bars are incremental contributions by learning, which implies that the total contribution of the imperfect information model is the sum of the blue and the green bar. Here, the full information model is *not* re-calibrated and the noise is shut down in the imperfect information model. Further, I shut down each mechanism one by one in both models.

pre-recession trough.

Table B2: Duration of Recovery of Unemployment Rate Across Recessions

Recession	Data	Full Information	Imperfect Information
1973-75	22	14	17
1981-82	24	17	21
1990-91	28	16	24
2001	24	14	21
2007-09	37	22	32

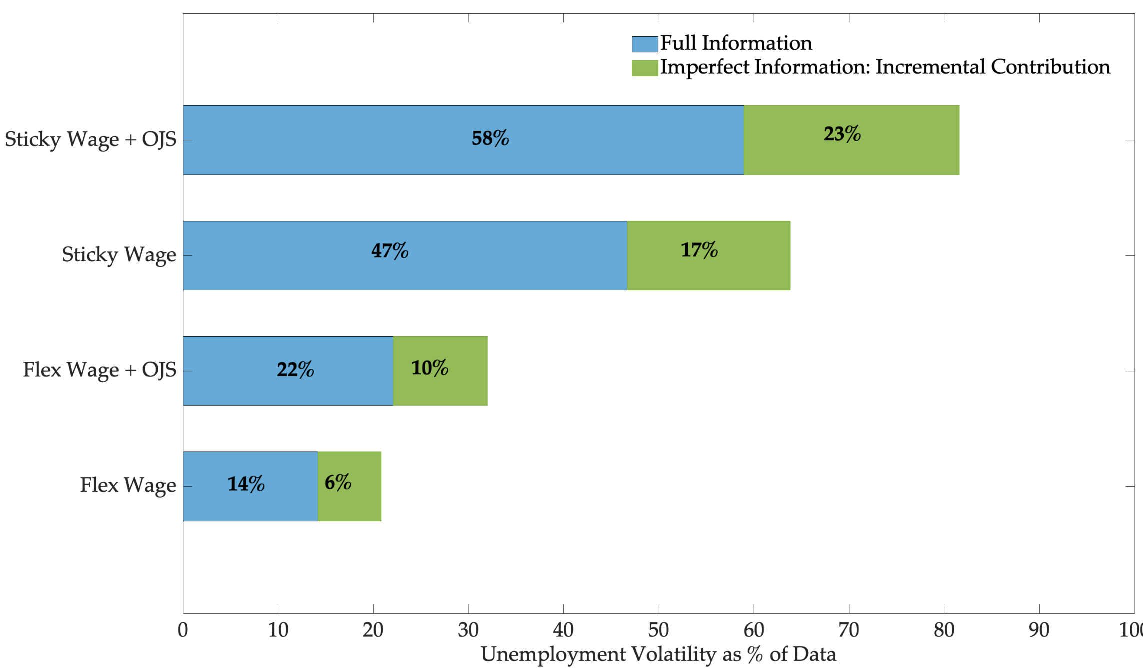
Note: This table reports the number of quarters it takes unemployment to return to pre-recession trough across five recessions between 1975-2019. The model is normalized to match the starting unemployment rate for each of the recessions. The imperfect information model is simulated each period with all three identified shocks from the VAR activated. For the full information model, only the persistent and the transitory shocks are incorporated each period. The full information model is then re-estimated to match the empirical impulse responses to the persistent TFP shocks.

Volatility In this section, I compare the unemployment volatility under various mechanisms with and without imperfect information. To highlight that learning contributes to volatility under each specification, I plot the unemployment volatility as a percent of the observed volatility in data in Figure B8. In the stacked bar graph, I compare full information benchmark to imperfect information model under 4 scenarios: a) flexible wages without on-the-job search (OJS), b) flexible wages with OJS, c) sticky wages without OJS, and d) sticky wages with OJS. I do not re-calibrate the full information model, but shut down noise in the imperfect information model.

Within the flexible wages without OJS framework, full Information framework accounts for approximately 14% of the unemployment volatility observed in the data. However, when introducing imperfect information, volatility is markedly amplified, bringing the cumulative total to around 20%. In the flexible wage with OJS environment, while full information accounts for about 22% of the volatility, imperfect information's contributes an additional 10% to the unemployment volatility.

Introduction of sticky wages with no OJS contributes significantly to the volatility and under full information, it encompasses nearly 47%. This is not a surprising result as sticky wages have long been proposed as a mechanism to match the observed volatility of unemployment (Shimer, 2005). However, it is important to note that learning contributes an additional 17%. Finally, when OJS is introduced along with sticky wages, the full information model can predict about 58% of the volatility in the data, but importantly, the cumulative impact of imperfect information catapults it to a significant 81%. This underscores the substantial amplification by imperfect information across wage-setting contexts.

Figure B8: Unemployment Volatility as a % of Data Across Models



Note: This figure plots the model implied standard deviation for the unemployment rate across models. Here, the full information model is *not* re-calibrated, but noise is shut down in the calibrated imperfect information model. Further, I shut down each mechanism one by one in both models.

Table B3 compares the business cycle statistics obtained by simulating the imperfect information model as well the re-calibrated full information model, to the statistics in the US economy from 1968-2019 across multiple labor market variables such as output (Y), unemployment rate (U), job vacancies (V), job-tp-job transitions ($E-E$), job transitions from unemployment to employment ($U-E$), and hiring rate. I compare full information benchmark to imperfect information model under 4 scenarios: a) flexible wages without on-the-job search (OJS), b) flexible wages with OJS, c) sticky wages without OJS, and d) sticky wages with OJS.

The imperfect information model outperforms the full-information model across all specifications, highlighting that learning is an important mechanism for volatility in the labor market.

Table B3: Business Cycle Statistics

	Data (SD)	Flex Wage , No OJS		Flex Wage , OJS		Sticky Wage , No OJS		Sticky Wage , OJS	
		Full Info	Imperfect Info	Full Info	Imperfect Info	Full Info	Imperfect Info	Full Info	Imperfect Info
Y	0.019	0.009	0.014	0.011	0.017	0.013	0.021	0.018	0.027
U	0.162	0.029	0.068	0.052	0.098	0.087	0.128	0.102	0.153
V	0.182	0.032	0.091	0.072	0.136	0.101	0.176	0.131	0.193
U-E	0.069	0.019	0.031	0.027	0.042	0.032	0.061	0.048	0.077
E-E	0.102	0.017	0.039	0.042	0.063	0.036	0.055	0.069	0.086

Note: This table reports standard deviation of key labor market variables in the model. The data here has been simulated from the model and HP-filtered (100,00).