Imperfect Information and Slow Recoveries in the Labor Market

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Abstract

The unemployment rate remains elevated long after recessions, a persistence standard search-and-matching models fail to explain. I show that noise shocks—expectational errors from noisy signals about productivity—constitute a novel channel generating this sluggishness. Using a structural VAR, I find unemployment would have recovered six quarters earlier absent such shocks. To interpret this evidence, I introduce imperfect information in a search-and-matching model, which successfully replicates the observed recoveries. Persistence arises through two channels: slow learning amplifies the effects of persistent productivity shocks, while noise shocks provide an additional, independent source of sluggishness—highlighting information frictions as an important driver of slow recoveries.

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1 Introduction

One of the long-standing challenges for conventional business cycle models has been to match the persistence in the recovery of the labor market, especially of the unemployment rate following recessions. In this paper, I document a new stylized fact: professional forecasters systematically overestimate the time that it takes unemployment to recover from a recession, suggesting that ex-ante they expect the recoveries to be even longer than observed. This systematic overestimation suggests the presence of information frictions, where agents misperceive the persistence of aggregate shocks and rely on noisy signals to form expectations. The presence of such frictions offer a potential mechanism to slow job creation and search activity, thereby generating a positive feedback cycle that lead to slower unemployment recoveries. To investigate such a channel, I estimate noise shocks, persistent TFP shocks, and transitory TFP shocks from a tri-variate VAR. I find that the noise shocks play an essential role in explaining the persistence of the labor market. I then incorporate the noise shocks into a model of labor search with imperfect information, and confirm that the presence of imperfect information is key for the model's success in matching the sluggishness of the unemployment rate during recoveries.

I begin by presenting a set of empirical facts using data on the unemployment rate and forecasts from the Survey of Professional Forecasters (SPF). It takes between 5 and 16 quarters for the unemployment rate in the United States to recover half of its recessionary increase, and more than 20 quarters to return to its pre-recession level. Using forecast data from the SPF, I next document that professional forecasters are even more pessimistic about the recovery than the realized data suggest. There is a consistent wedge between expected and actual unemployment rates across recessions, with forecasts predicting even slower recoveries. This pattern suggests that forecasters, like agents in the economy, may lack perfect information about the aggregate state and instead rely on noisy signals to form expectations about whether changes in fundamentals are persistent or transitory. Such misperceptions can influence key economic decisions, such as hiring and investment, thereby contributing to a sluggish labor market recovery.

To understand these facts, I build upon the identification strategy from Chahrour, Nimark, and Pitschner, 2021 and Enders, Kleemann, and Müller, 2021, to estimate noise shocks (shocks that arise from changes in expectations without any changes in fundamentals), persistent TFP shocks, and transitory TFP shocks from a VAR in utilization-adjusted TFP, real GDP growth, and nowcast errors of professional forecasters. The noise shocks are identified using sign restrictions with the assumption that the noise shocks, by definition, must affect expectations more than the fundamentals. I further refine this strategy by imposing a zero restriction that rules out any contemporaneous effect of noise shocks on actual TFP. Additionally, to distinguish persistent from transitory TFP shocks, I identify the persistent component as the shock that maximizes the long-run forecast error variance of TFP. I document two key findings from this exercise. First, labor market variables, including unemployment, vacancies, and job-finding rates, respond significantly to the estimated noise shocks, which account for roughly one-third of their variation at business cycle frequencies. Second, in the absence of noise shocks, unemployment would have recovered to its pre-recession level an average of six quarters earlier.[1] These findings suggest

[1] While it takes on average 17 quarters for unemployment rate to recover 50% of its recessionary rise since the beginning of the recession, it would be 11 quarters in the absence of noise shocks. Noise shocks also dampened job-finding rates and vacancies.

a critical role for the noise shocks in the recovery of the labor market and indicate the presence of information frictions.[2]

To study the role of noise shocks in driving labor market persistence, I embed imperfect information (Lorenzoni, 2009) into a model of equilibrium unemployment featuring endogenous search effort, on-the-job search, and sticky wages à la Gertler, Huckfeldt, and Trigari, 2020.[3] The model includes two fundamental productivity shocks, transitory and persistent, but agents cannot distinguish between them. Instead, they observe aggregate productivity and receive a noisy signal about its persistent component, which they use to form beliefs about future productivity. Noise shocks add complexity by making it harder for agents to discern whether observed changes reflect true persistent shocks or simply noise in the signal. The calibrated model successfully accounts for the sluggish labor market recovery: relative to a model with full information, the model with imperfect information generates an additional six quarters (30%) of elevated unemployment following recessions.

There are two channels for the success of the model. First, learning under imperfect information generates persistence endogenously: it takes time for agents to learn whether a shock is persistent or not, leading to an initial under-reaction. Wage stickiness further delays this dynamics, as infrequent renegotiation makes agents hesitant to revise wages without fully knowing the shock's persistence. This interaction between imperfect information and wage rigidity is novel and central to the persistence mechanism. Second, noise shocks themselves may prolong recoveries, as agents mistake them for actual productivity shocks and respond to them accordingly, even though the fundamentals are unchanged. Together, these mechanisms successfully account for the persistence in the unemployment dynamics following downturns.

Further, the model successfully replicates the systematic overestimation of medium-run unemployment by professional forecasters observed in the data. This overshooting arises endogenously from agents' misperceptions driven by noise shocks and cannot be replicated in models with only structural productivity shocks, which, by definition, imply that actual outcomes exceed expectations and thus tend to generate forecast under-reaction, a well-known limitation of standard macroeconomic models. This ability to match both the persistence in unemployment and the forecast errors constitutes not only a success for the model but is also a key empirical validation of the imperfect information channel.

This paper builds on the literature documenting the persistence of unemployment following recessions and the difficulty conventional business cycle models face in explaining this fact, as documented by Cole and Rogerson (1999), and more recently by Hall and Kudlyak (2022) and Ferraro (2023). Slow labor market recoveries have been a consistent feature of postwar recessions, yet there remains no unified consensus on their underlying drivers. Prominent explanations include job polarization (Jaimovich and Siu, 2020), organizational restructuring following long expansions (Berger et al., 2012; Koenders, Rogerson, et al., 2005), changes in the persistence of business cycles (Bachmann, 2012; Panovska, 2017),

[2]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.

[3]Pissarides (2009) critiques models that rely on sticky wages for new hires. Several papers provide responses to this critique: Gertler, Huckfeldt, and Trigari (2020) show that staggered Nash bargaining can reconcile wage stickiness with data on unemployment fluctuations; Grigsby, Hurst, and Yildirmaz (2021) and Hazell and Taska (forthcoming) present empirical evidence of wage rigidity in administrative and vacancy-level data. An alternative view is offered by Kudlyak (2014), who emphasizes the cyclicality of the user cost of labor rather than wages directly.

the rising importance of technology shocks since the mid-1980s (Barnichon, 2010b), extended unemployment insurance (Mitman and Rabinovich, 2019), and the convergence of female employment (Fukui, Nakamura, and Steinsson, 2023). These explanations focus on evolving fundamentals. In this paper, I instead document a novel role for noise shocks that arise when agents face imperfect information about changes in fundamentals. This mechanism complements the existing literature by showing how informational frictions—when embedded in a search and matching model—rather than changes in fundamentals themselves, can generate the sluggish unemployment recoveries observed in the data.

A separate strand of the literature emphasizes asymmetric labor market dynamics, where recessions trigger sharp rises in unemployment but recoveries are slow. This asymmetry has been modeled through endogenous job separation (Andolfatto, 1997) and worker heterogeneity in productivity (Ferraro, 2018). These models generate slow recoveries by amplifying shocks through non-linearities in the labor market. My paper instead documents new evidence that the underlying driving forces differ systematically between recessions and expansions, pointing to a complementary mechanism. In particular, I show that professional forecasters systematically overestimate unemployment during recoveries—a stylized fact that conventional models cannot replicate.

This paper therefore connects to the long-standing research agenda on information frictions in macroeconomics, dating back to Lucas (1972, 1975) and developed further in Angeletos and La'O (2010, 2013), Blanchard, L'Huillier, and Lorenzoni (2013) and Angeletos, Collard, and Dellas (2020). These theories demonstrate how noisy signals about fundamentals can distort beliefs and propagate shocks. My contribution is to embed such information frictions in a search-and-matching model of the labor market, thereby linking them to the persistence of unemployment, an application not previously explored in this literature. In parallel, an empirical literature has developed methods for identifying noise shocks from macroeconomic data, most recently Chahrour, Nimark, and Pitschner (2021) and Enders, Kleemann, and Müller (2021). I advance this empirical agenda by refining their identification strategy: I impose additional restrictions and also identify persistent and transitory productivity shocks separately, allowing me to quantify the distinct role of noise shocks in driving labor market recoveries. Taken together, these contributions bridge theoretical and empirical work on information frictions, offering a comprehensive account of how noisy signals shape both beliefs and labor market dynamics.

Within the labor market literature, Venkateswaran (2014) shows that firms' inability to disentangle aggregate from idiosyncratic shocks can generate volatility far larger than in standard search models. In that framework, firms misattribute part of aggregate shocks to idiosyncratic factors and, because they respond more strongly to the latter, hiring fluctuations are amplified, helping resolve the Shimer (2005) volatility puzzle. My paper complements this by focusing on a different friction: imperfect information about the persistence of aggregate shocks. Whereas Venkateswaran (2014) emphasizes volatility driven by misperceptions of the source of shocks, I show that noise shocks tied to misperceptions of persistence generate sluggish labor market recoveries and systematic forecast errors.

More recent work by Faccini and Melosi (2022) and Morales-Jiménez (2022) quantitatively assesses the importance of information frictions in labor market dynamics. Further, Kozlowski, Veldkamp, and Venkateswaran (2020) and D'Agostino, Mendicino, and Puglisi (2022) show that imperfect information about the distribution of shocks can produce persistent effects from transitory disturbances, particularly during the Great Recession. My analysis complements these papers by combining new empirical evidence—systematic forecast errors by professional forecasters—with a structural model that demonstrates how noise shocks and imperfect information jointly account for sluggish labor market recoveries across recessions.

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

2 Unemployment Recoveries and Noise Shocks

In this section, I first document the sluggish recovery of unemployment in the United States between 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 the 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. Having established these facts, I then proceed to identify noise shocks using nowcast errors in Section 2.1, where I discuss in detail the identification strategy.

I then document in Section 2.2, that these noise shocks have a significant impact on aggregate labor market outcomes, including unemployment, vacancies and job-finding rates. Specifically, I document the following empirical facts. First, noise shocks have persistent effects on the dynamics of the labor market. 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. The impulse responses suggest that firms and workers are learning under imperfect information. Second, a forecast error variance decomposition shows that noise shocks account for about one-third of the fluctuations in the key labor market variables. Third, a historical shock decomposition shows that the noise shocks contribute significantly to the recovery of the unemployment rate: absent noise shocks, it takes unemployment an additional 6 quarters on average to recover 50% of its recessionary increase.

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, Karahan, and Şahin, 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

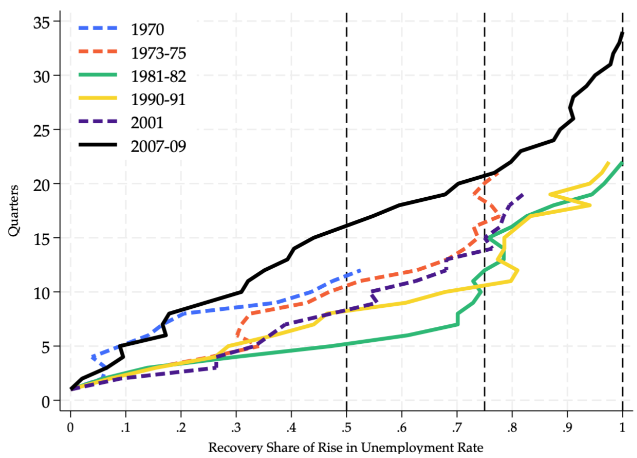


Table 1: Unemployment Recovery Across Recessions

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

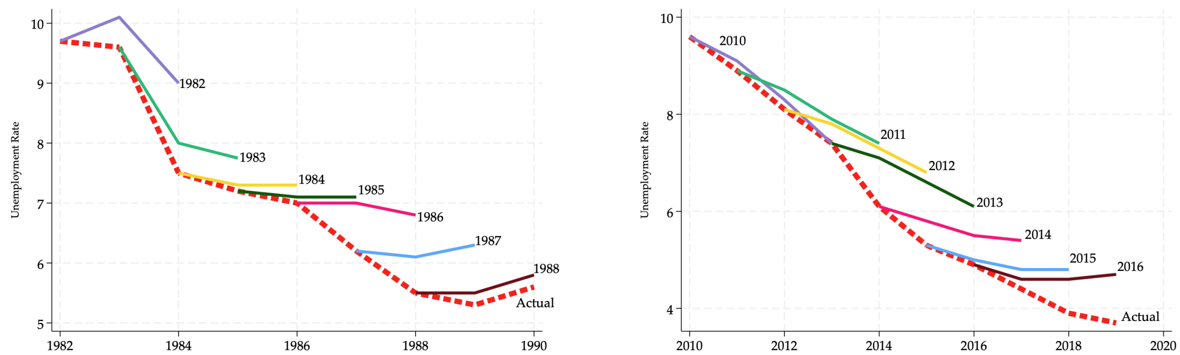
Note: Figure (1) and Table (1) report the number of quarters taken to recover 25%, 50%, 70% and 100% of the rise in the unemployment rate from its peak across recessions between 1968-2019, except the recession in 1980 which was quickly followed by the downturn in 1981-82. The NBER Cycle is the duration 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.[4] 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

[4]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.

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.

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, Laubach, and Williams, 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, Kleemann, and Müller, 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 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.

2.1 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, arises 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. I 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 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 represent changes in the signal that do not stem from actual productivity shocks. The aim is to 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.[5] 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, L'Huillier, and Lorenzoni, 2013).

[5] 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.

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, $B_j = A_0^{-1} A_j$, $u_t = A_0^{-1} \epsilon_t$. $var(\mathbf{u}_t) = E(\mathbf{u}_t \mathbf{u}_t') = \Sigma = \mathbf{A_0^{-1}}(\mathbf{A_0^{-1}})'$ is the $n \times n$ variance-covariance matrix of reduced-form errors. Let $\boldsymbol{\phi} = (\mathbf{B}, \Sigma)$ 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.

   (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.[6]

   (c) Noise shocks contemporaneously affect nowcast errors in the opposite direction from GDP growth. In other words, noise shocks are assumed to move expectations about 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, Kleemann, and Müller, 2021 and Chahrour, Nimark, and Pitschner, 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, L'Huillier, and Lorenzoni, 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:

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

[6] 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.

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 finite 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 E. Sims, 2021 in the 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 $I_{-j} = 1, \ldots, k$ 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 $\mathbf{IR}^h = \mathbf{C}_h(\mathbf{B})\Sigma_{\mathbf{tr}}\mathbf{Q}$. The sign restrictions are represented by $\boldsymbol{S}_j(\phi)\boldsymbol{q}_j \geq \mathbf{0},$ for $j \in \mathcal{I}_{\mathcal{S}}$. Let $CEFEV_j^i(H)$ denote the factor error variance (% contribution) at horizon H of variable i explained by the j^{th} structural shock.

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

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

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

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

subject to

$$\begin{aligned}
&(8) & \boldsymbol{q}_1'(1,3) &= 0 \\
&(9) & \boldsymbol{S}_j(\phi)\boldsymbol{q}_j &\geq \mathbf{0}, \text{ for } j \in \mathcal{I}_{\mathcal{S}} \\
&(10) & q_1' q_1 &= 1
\end{aligned}$$

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.[7] 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 suggests that forecasters do

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

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.

2.2 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.

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

$$y_{t+h} = \alpha^j_h + \beta^j_h u^j_t + \sum_{p=1}^{P} \gamma^j_p \omega_{t-p} + \mu^j_{h,t+h} \tag{11}$$

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

Following Barnichon and Brownlees, 2019, one can approximate $\beta^j_h \approx \sum_{k=1}^{K} b^j_k B^j_k(h)$ using a linear B-splines basis function expansion in the forecast horizon h. Thus, the corresponding smooth linear projections can be written as Equation 12.

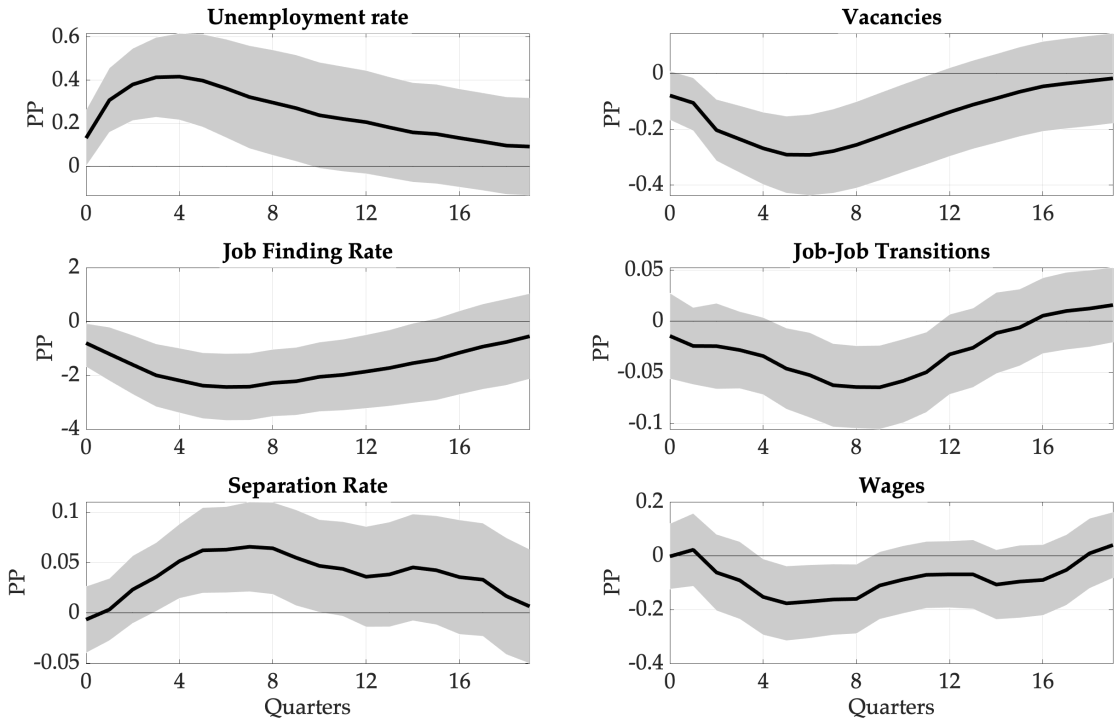
$$y_{t+h} \approx \sum_{k=1}^{K} a^j_k B_k(h)^j + \sum_{k=1}^{K} b^j_k B^j_k(h) u^j_t + \sum_{p=1}^{P} \sum_{k=1}^{K} c^j_{pk} B^j_k(h) \omega^j_{t-p} + \mu^j_{h,t+h} \tag{12}$$

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^j_t is the residual error for each regression. All labor market data are from

Current Population Survey and JOLTS for vacancies and hiring rate.[8] Figures 3 and 4 show the impulse responses of the labor market variables to standardized 1 standard deviation negative noise and persistent TFP shocks.[9]

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.

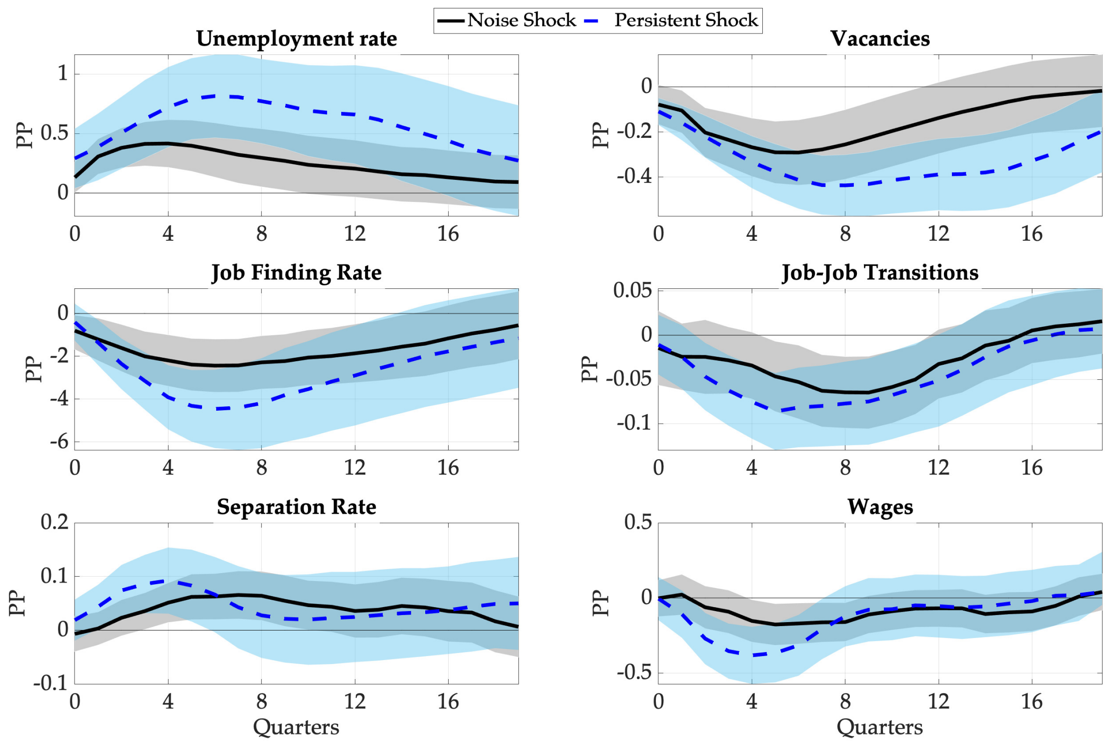
Noise shocks have a significant and persistent effect on unemployment, vacancies, *UE*, *EE*, as well as the hiring rate for up to 10 quarters. The negative effect on wage growth is delayed, although weak, indicating that wages are sluggish. Unemployment rises by 0.6 percentage points in response to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

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

[8] The results are consistent with using an Autoregressive Distributed Lag (ADL)pecification for local projections.
[9] Response to the transitory TFP shocks is documented in Appendix Figure A10.

respond as if faced with an actual negative productivity shock. Firms decrease their hiring and increase layoffs. As there are fewer jobs to be matched 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 increases, resulting in a decline in unemployment.

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.

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 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:

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

where $\nu_{t+h|t-1}$ 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 (C. A. 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.

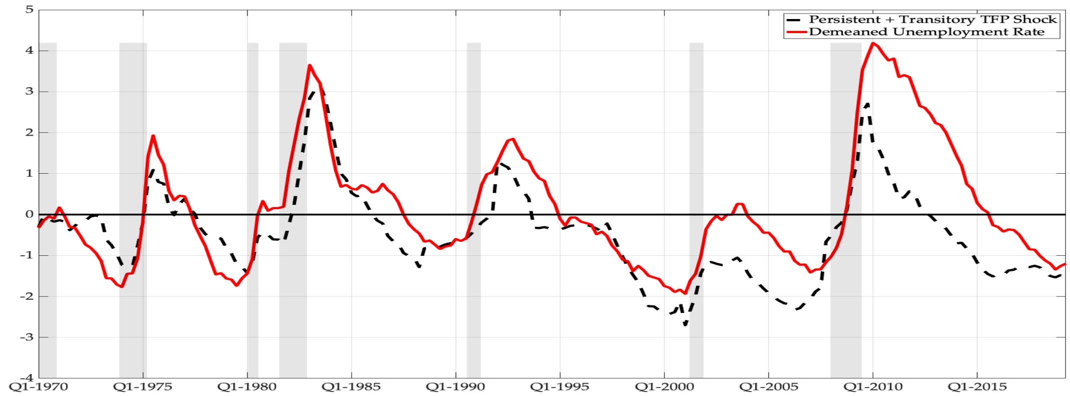
An examination of the recessions in 1990, 2001, and 2007-09 reveals that the productivity shocks are insufficient to completely explain the fluctuations in the unemployment rate, vacancy postings and job finding rates. The productivity shocks predicted a faster recovery across these recessions and a 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.

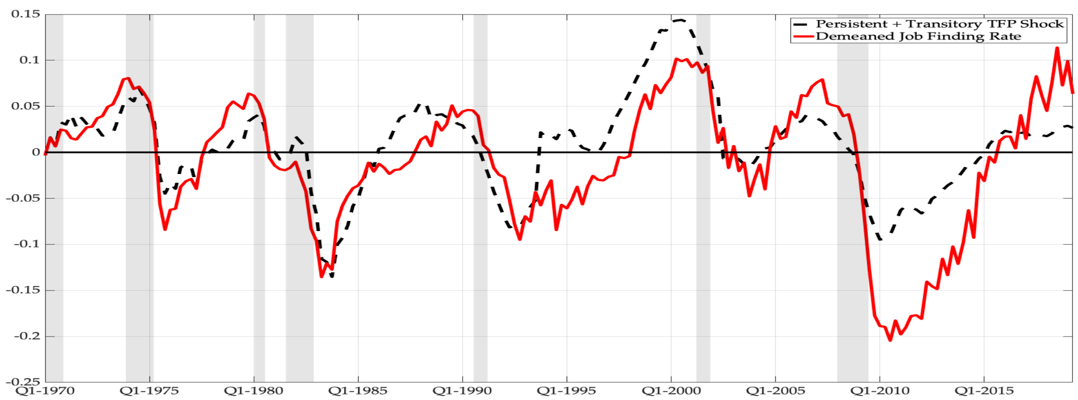
An aggregate assessment of these findings implies that during these recessions, noise shocks led to a mis-estimation of the persistence of the shock by economic agents. This misperception led to an overestimation of the actual persistence of the shock, thereby influencing decisions concerning employment 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,

Figure 5: Historical Contribution of Persistent and Transitory TFP Shocks

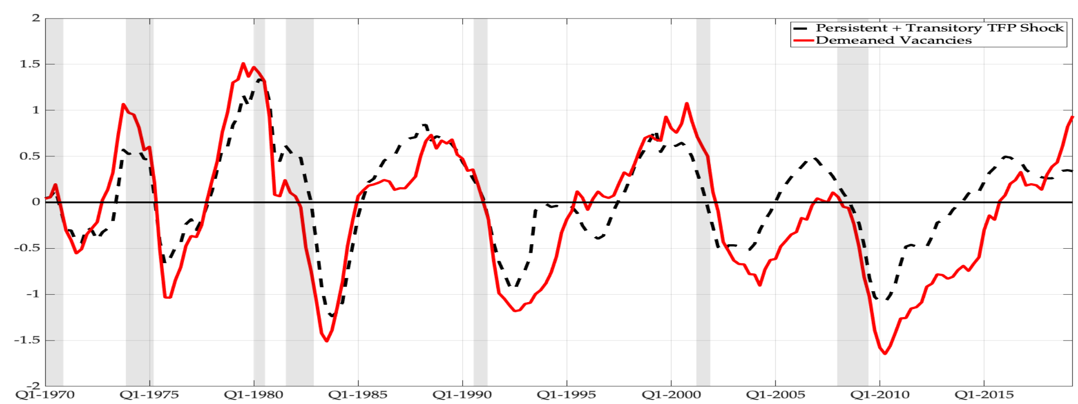
(a) Unemployment Rate



(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.

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 account for about 35% of the 50% of the rise in unemployment and on average noise shocks account for 32% 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.

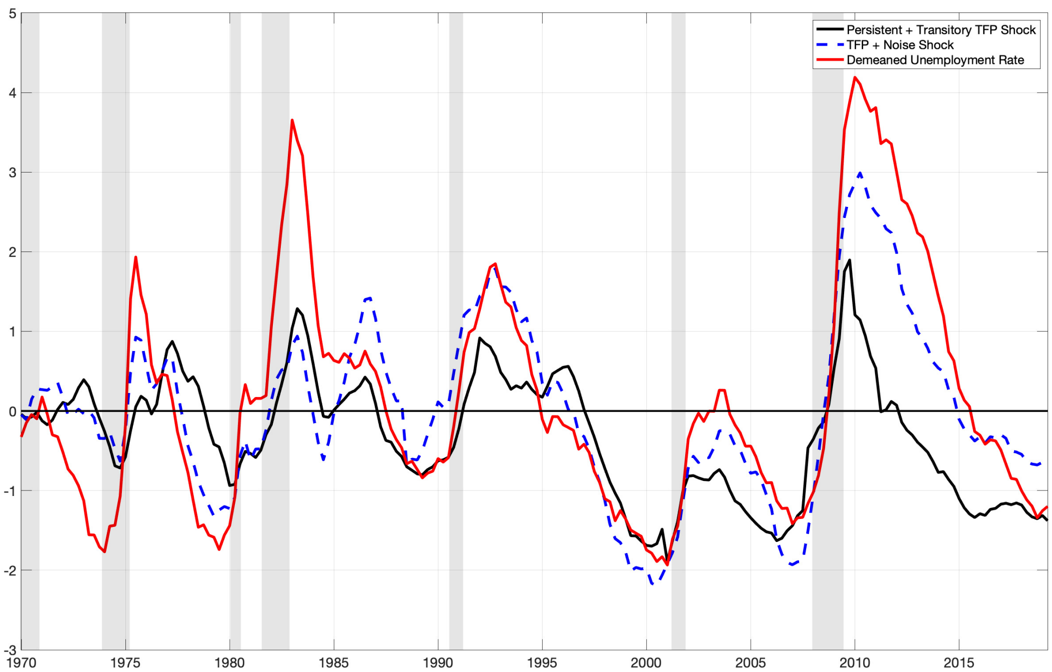
2.3 Robustness: Inclusion of Unrestricted Shocks

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 include 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.

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

Once again, I assume that ϵ_t maximizes the forecast error variance of TFP at a long-run horizon. I

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.

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 the unemployment rate. However, in the 1973–75, as well as the 1980–81 and 1982–83 recessions, the contribution of the 4th shock is the highest in explaining the movement in the 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.

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.

3 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.[10] 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 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, Huckfeldt, and Trigari, 2020 who introduce staggered wage contracting and allow for on-the-job search with variable intensity. The primary reason for introducing 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 of unemployed workers is given by:

$$\begin{aligned} \bar{u}_t &= 1 - \bar{g}_t - \bar{b}_t \\ \bar{g}_t &= \int_i g_t \, di \\ \bar{b}_t &= \int_i b_t \, di \end{aligned}$$

where $\bar{g}_t$ 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 s_{ut}. Employed workers in a bad match also search on the job so that they can move up the ladder and match with a good

[10] As Cole and Rogerson, 1999 note, the DMP model can account for business cycle facts only if the average duration of non-employment spells is nine months or longer, which is quite high relative to that observed in the data.

job. They search with endogenous search intensity s_{bt}. 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 movements to other bad jobs are eliminated.[11] Search is costly and the cost of searching is characterized by

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

where s_{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 the 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 are therefore given by the search-intensity-weighted sum of searchers

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

The aggregate number of matches is 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 given, respectively, as follows:

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

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

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

[11] As Gertler, Huckfeldt, and Trigari, 2020 explain, the expected gain from a lateral move is quantitatively trivial and can be ruled out with a small moving cost.

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, $\frac{\sigma s_{bt}\bar{b}_t}{\bar{s}_t}$, 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 is:

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

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 laws of motion for the good and bad matches, respectively:

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

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

Total good matches next period are the 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, the total number of bad matches next period is the 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 and household's decision problems are based upon is as follows. At the beginning of period t, given the information set $\mathcal{I}^{t-1}$, firms choose vacancies and capital, and households choose consumption, savings and search intensities. During period t, aggregate and idiosyncratic productivity shocks are realized and production takes place given these predetermined choices. Next, match-specific separation shocks are realized. Finally, surviving workers search and new matches are formed, which become productive in period $t+1$.

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.

Information sets and expectations. At the start of period t, agents' information set is denoted by $\mathcal{I}_{t-1}^{\text{end}}$, which contains the history of aggregate productivity and signals up to $t-1$, as well as past endogenous variables:

$$\mathcal{I}_{t-1}^{\text{end}} = \{z_\tau, \hat{s}_\tau, \text{ endogenous variables at } \tau \leq t-1\}.$$

Expectations taken at the start of period t are written as

$$\mathbb{E}_t[\cdot] \equiv \mathbb{E}[\cdot \mid \mathcal{I}_{t-1}^{\text{end}}].$$

These expectations determine all period-t decisions. At the end of period t, after the realization of aggregate productivity z_t and the public signal $\hat{s}_t$, the information set becomes

$$\mathcal{I}_t^{\text{end}} = \mathcal{I}_{t-1}^{\text{end}} \cup \{z_t, \hat{s}_t\}.$$

Beliefs about the permanent component x_t are summarized by the posterior

$$x_{t|t} \equiv \mathbb{E}[x_t \mid \mathcal{I}_t^{\text{end}}],$$

and the prior used at the start of period $t+1$ is

$$x_{t+1|t} = \rho\, x_{t|t}.$$

Thus, period-t controls are functions of the prior $x_{t|t-1}$ and other predetermined state variables, while the updated belief $x_{t|t}$ affects decisions only from period $t+1$ onward.

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 $z_t = \log Z_t$. 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 noise component 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. The 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 $x_{t|t} \equiv \mathbb{E}[x_t \mid \mathcal{I}_t^{\text{end}}]$ denote the posterior belief about x_t at the end of period t, after observing $(z_t, \hat{s}_t)$. The corresponding prior at the start of period t is

$$x_{t|t-1} \equiv \mathbb{E}_t[x_t] = \mathbb{E}[x_t \mid \mathcal{I}_{t-1}^{\text{end}}].$$

Agents update their beliefs about x_t in a Bayesian manner using a Kalman filter.

Thus, the dynamics of $x_{t|t}$ are

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

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. Decisions at date t are functions of the prior belief $x_{t|t-1}$, which is formed at the beginning of t based on $\mathcal{I}^{t-1}$. The updated belief $x_{t|t}$ is used only from period $t+1$ onward.

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

1. Firms and workers form expectations at the beginning of t with information set $\mathcal{I}^{t-1}$ and choose k_t, v_t, s_{ut}, s_{bt} and other controls as functions of this information set.

2. Firms and workers make their decisions for time period t (production, hiring and separation) given these predetermined choices.

3. The public signal $\hat{s}_t$ is revealed as is the value of z_t. However, firms and workers do not update or change their decisions in time period t (pre-commitment); the new information is only used from period $t+1$ onward.

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 $z_t, y_t, c_t, u_t, v_t, \bar{s}_t, w_t$ and learn about the true aggregate productivity. However, assuming that signal extraction is costly, agents only use the public signal to learn and make decisions. This assumption is similar to Woodford, 2001, Mankiw and Reis, 2002 and Angeletos, Iovino, and Jennifer, 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 $\hat{s}_{t-1}$. 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 $\mathcal{I}^{t-1}$.*[12]

[12] 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 contains 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.

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 the 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 firm's decision problem is therefore to choose k_t and χ_t to maximize the value of the firm, 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 the rental rate. Firms 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 laws of motion 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:

$$k_t \quad : \quad Z_t \zeta \left(\frac{l_t}{k_t} \right)^{1-\zeta} - r_t = 0 \tag{27}$$

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

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 the hiring rate can be solved to get the vacancies v_t since $\chi_t = q_t v_t / l_t$. Each firm optimizes its hiring rate and in equilibrium, total vacancies are given by summing across all firms, $\bar{v}_t = \int_0^1 v_{it}\, di$.

Household's Problem There is a unit measure of families, each with a measure-one mass 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 $\mathcal{I}^t$. 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:

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

subject to

$$\begin{aligned}
\bar{c}_t + \bar{k}_{t+1} + c(s_{bt})\,\sigma\bar{b}_t + c(s_{ut})\bar{u}_t &= \bar{w}_t\bar{g}_t + \phi\bar{w}_t\bar{b}_t + \bar{u}_t\,b + (1-\delta+r_t)\,\bar{k}_t + T_t + \Pi_t, \\
\bar{g}_{t+1} &= \sigma\bar{g}_t + \xi p_t\bar{s}_t, \\
\bar{b}_{t+1} &= \sigma\big(1 - s_{bt}\xi p_t\big)\,\bar{b}_t + (1-\xi)p_t\bar{u}_t.
\end{aligned}$$

The associated stochastic discount factor is

$$\Lambda_{t,t+1} = \beta\,\frac{1/\bar{c}_{t+1}}{1/\bar{c}_t},$$

which is used in firms' and workers' intertemporal problems.

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. The flow benefit from unemployment is b. An unemployed worker searches with an endogenous search intensity s_{ut}. The value of unemployment is given by:

$$U_t = \max_{s_{ut}} \mathbb{E}_t\left\{ b - c(s_{ut}) + \Lambda_{t,t+1}\Big[\big(1 - s_{ut}p_t\big)\,U_{t+1} + s_{ut}(1-\xi)p_t V_{t+1}^b + s_{ut}\xi p_t V_{t+1}^g\Big] \;\Big|\; \mathcal{I}^{t-1}\right\}. \tag{30}$$

Here, in the current period, an unemployed worker receives b, net of search costs. In $t+1$, with probability $(1-p_t)s_{ut}$, an unemployed worker does not find a job and remains unemployed in $t+1$.[13] Unemployed workers find it optimal to accept either a bad or a good match if they receive one, as long as the wages are greater than their outside option.

Employed Workers Employed workers earn a wage w_j while employed at firm j. The workers in a bad match search on the job with endogenous intensity s_{bt} and are matched with another firm with probability $s_{bt}p_t$. 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.

The value of being employed for a worker in a good match is given by

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

A worker in a good match earns the wage w_t 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, or she continues being in a good match in the subsequent period.

[13]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.

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

$$V_t^b = \max_{s_{bt}} \mathbb{E}_t \Bigg\{ \phi w_t - \sigma c(s_{bt}) + \Lambda_{t,t+1} \Big[(1-\sigma) U_{t+1} + \sigma \big(1 - s_{bt}\, \xi p_t\big) V_{t+1}^b + \sigma s_{bt} \xi p_t V_{t+1}^g \Big] \,\Big|\, \mathcal{I}^{t-1} \Bigg\}. \tag{32}$$

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 ϕw_t, and if the worker survives within the firm, which occurs with probability σ, she searches with variable intensity s_{bt}, and since search is costly, she pays the cost of searching. In the next period, if she is hit by the separation shock she flows into unemployment. If she remains employed in the bad match, the worker might be matched with a good job in which case she moves 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.[14] 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:

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

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 probability λ, 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 household's relative bargaining power. Now, to a first-order approximation, the evolution of average wages can be written as

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

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.[15]

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:

$$\bar{y}_t = \bar{c}_t + \bar{k}_{t+1} - (1-\delta)\bar{k}_t + \frac{\kappa}{1+\eta_h} \int_i \chi_t^{1+\eta_h} l_t \, di + c(s_{bt}) \, \sigma \bar{b}_t + c(s_{ut}) \bar{u}_t \tag{36}$$

The government funds unemployment benefits through lump-sum transfers:

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

Equilibrium The aggregate state of the economy is defined by $\Omega = \{l, g, b, k, z, x^{\mathcal{T}}, a^{\mathcal{T}}\}$. 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 $\{\chi_t, s_{ut}, s_{bt}, \bar{k}_{t+1}, \bar{c}_t, \bar{g}_t, \bar{b}_t\}$, (iv) the density function of composition and wages across workers dG_t, a transition function $Q_{t,t+1}$, and a law of motion for the economy Π_t, such that given the law of motion for exogenous variables z_t, x_t and a_t:

1. households optimize such that $\bar{c}_t$, $\bar{k}_{t+1}$ satisfy the optimality conditions;
2. optimal search and hiring: s_{bt}, s_{ut}, χ_t optimize the Bellman equations for V_t^b, U_t, J_t;
3. the wage w_t^N satisfies the Nash bargaining rule and w_{t+1} is given by (35);
4. all markets clear: the rental market for capital clears, households optimize consumption and search intensities, and firms optimize 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 $Q_{t,t+1}$;

[15]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 discounted 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.

6. at each point in time, agents' beliefs are determined by their information set $\mathcal{I}^{t-1}$ and 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 the theoretical framework is twofold. First, to assess whether introducing imperfect information improves the prediction of the duration of the 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: a persistent and a transitory productivity shock. As there is no information friction, 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 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.

Solution Method. To solve the model, I follow the approach in Gertler, Huckfeldt, and Trigari (2020). I first compute the deterministic steady state of the economy under imperfect information and then log-linearize the equilibrium conditions around this steady state, including the firms' optimality conditions, the household Euler equation, the search and matching block, the wage-contracting equations, and the laws of motion for the composition of matches. The resulting linear rational expectations system can be written in the form $\Gamma_0 y_t = \Gamma_1 y_{t-1} + \Psi \varepsilon_t$, where y_t collects the relevant endogenous variables and ε_t is the vector of structural shocks. I solve this system using the Anderson–Moore (AIM) algorithm, which yields the unique stable solution for the policy functions. The imperfect-information structure is incorporated by augmenting the state vector with the agents' filtered beliefs about the permanent component of productivity and applying a standard Kalman filter to the linear state-space representation, given the signal process for $\hat{s}_t$. This yields decision rules expressed in terms of the perceived state, which I use to simulate the model, construct impulse responses, and compute the moments used in the calibration and estimation exercises.

4 Parameterization and Estimation

I estimate the parameters in the model at a quarterly frequency using a three-step procedure. First, I fix the parameters $\{\beta, \delta, \zeta, \omega, \lambda, \alpha, \eta_h, \rho\}$ to widely accepted values from the literature. Then, I estimate

Table 3: Externally Fixed Parameter Values

Parameter	Interpretation	Value	Source
β	Discount factor	0.99	Shimer, 2005
δ	Depreciation rate	0.025	Gertler and Trigari, 2009
ζ	Capital share in production	0.33	Gertler, Huckfeldt, and Trigari, 2020
ω	Search-cost curvature parameter	3.60	Faberman et al., 2022
η	Worker's bargaining power	0.50	Shimer, 2005
λ	Probability wage contract is not renegotiated	0.75	Gertler, Huckfeldt, and Trigari, 2020
α	Elasticity of matches w.r.t. searchers	0.40	Gertler, Huckfeldt, and Trigari, 2020
η_h	Hiring cost convexity	2.40	Merz and Yashiv, 2007
ρ	AR(1) coefficient of permanent productivity x_t	0.949	Shimer, 2005

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

$\{\Psi, \kappa, \mu, \sigma, \phi, b, \xi\}$ by targeting unconditional stationary moments using the simulated method of moments. Finally, the remaining parameters $\{\sigma_\epsilon, \sigma_\nu, \rho_a, \mathcal{K}\}$ are estimated to match the impulse responses of the unemployment rate, vacancies, outflows 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. This exercise yields a signal-to-noise ratio of 0.23, which is consistent with values reported in the literature.

Table 3 summarizes the externally fixed parameters. I calibrate the capital share $\zeta = 0.33$, the discount factor $\beta = 0.99$, and the depreciation rate $\delta = 0.025$ to widely accepted values in the business-cycle literature. The hiring cost convexity parameter is set to $\eta_h = 2.40$ following Merz and Yashiv (2007), which implies a degree of curvature in hiring costs consistent with their estimates.

Targeting Unconditional Moments. As a first step, I target the steady-state unemployment rate, unemployment-to-employment transitions, job-to-job transitions and the 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, b, to match the relative value of non-work to work activity $\bar{u}_T = 0.71$ following Hall and Milgrom (2008).[16]

The efficiency parameter Ψ is chosen such that the steady-state unemployment rate in the model matches the average unemployment rate in the data for 1968–2019 and takes a value of 0.49. The hiring cost parameter κ determines the resources that firms invest in 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 $\tilde{p}$. Furthermore, a higher search cost implies a lower *EE* probability and hence the search cost parameter μ is chosen to match the *EE* probability; it takes the value $\mu = 0.082$.

The job-survival probability σ is chosen so that the implied separation probability $1 - \sigma$ matches the E–U transition probability. The steady-state productivity from a bad job, ϕ, is targeted to match the change in wages of workers who make job-to-job transitions. The ratio of bad jobs to good jobs is held

[16] Following Hall and Milgrom (2008), I choose b such that the steady-state value of non-work relative to work is $\bar{u}_T = 0.71$ in the model.

Table 4: Parameters Estimated by Simulated Method of 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 the Simulated Method of Moments to target key stationary moments in the data: the unemployment rate, the unemployment-to-employment transition rate, the job-to-job transition rate, the employment-to-unemployment separation rate, and the wage change of workers who make job-to-job transitions. These moments are calculated over the sample period 1968Q4–2019Q4 using the CPS.

constant and is calibrated following Gertler, Huckfeldt, and Trigari (2020).[17] I further calibrate ξ to match the average share of job transitions involving positive wage changes out of total job flows, targeting a value of 0.527 following Gertler, Huckfeldt, and Trigari (2020). The corresponding value is $\xi = 0.24$. A lower probability of finding a good job corresponds to a higher steady-state value of the bad-to-good worker ratio and hence a higher average share of bad-to-good flows. The resulting set of parameters estimated by SMM is reported in Table 4.

Information Parameters: Impulse Response Matching. I estimate the information parameters by matching model-implied responses following a noise shock and a TFP shock to their counterparts in the empirical exercise (Christiano, Eichenbaum, and Evans, 2005; Rotemberg and Woodford, 1997). The targets are the responses of the unemployment rate, the *UE* rate and the *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 across variables and horizons, and let $f_m(\Theta)$ denote the corresponding model-generated IRFs, where Θ is a vector of model parameters. The optimization problem is

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

where $\Theta = \{\sigma_\epsilon^2, \sigma_\nu^2, \rho_a, \mathcal{K}\}$ and $\mathcal{K}$ is the signal-to-noise ratio. The weight matrix W is the inverse of the variance–covariance matrix of the empirical IRF estimates.[18]

The result of this estimation process is documented in Table 5, with standard errors calculated

[17] Specifically, following Gertler, Huckfeldt, and Trigari (2020), the steady-state ratio of bad to good jobs satisfies

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

where p^{EE} and p^{EU} are the probabilities of E–E and E–U transitions, respectively, and λ_e is the job-survival parameter in their framework. In my calibration, I choose ξ so that the implied ratio $\bar{b}/\bar{g}$ matches this target given the model-implied transition probabilities.

[18] The objective function is a generalized method-of-moments criterion in which the moments are the IRFs. The weighting matrix weights deviations by the precision of the empirical estimates.

Table 5: Estimated Parameters from IRF Matching

Parameter	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_a	Persistence of noise component a_t	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.

using the delta method (Guerron-Quintana, Inoue, and Kilian, 2017). The estimated signal-to-noise ratio is $\mathcal{K} = 0.23$, indicating that only a modest share of the variation in the signal reflects true innovations to the permanent component. In the calibrated model, the implied standard deviation of the transitory productivity shock is $\sigma_\eta = 0.192$, so that learning about the persistent component of productivity is gradual and agents adjust their beliefs only slowly.

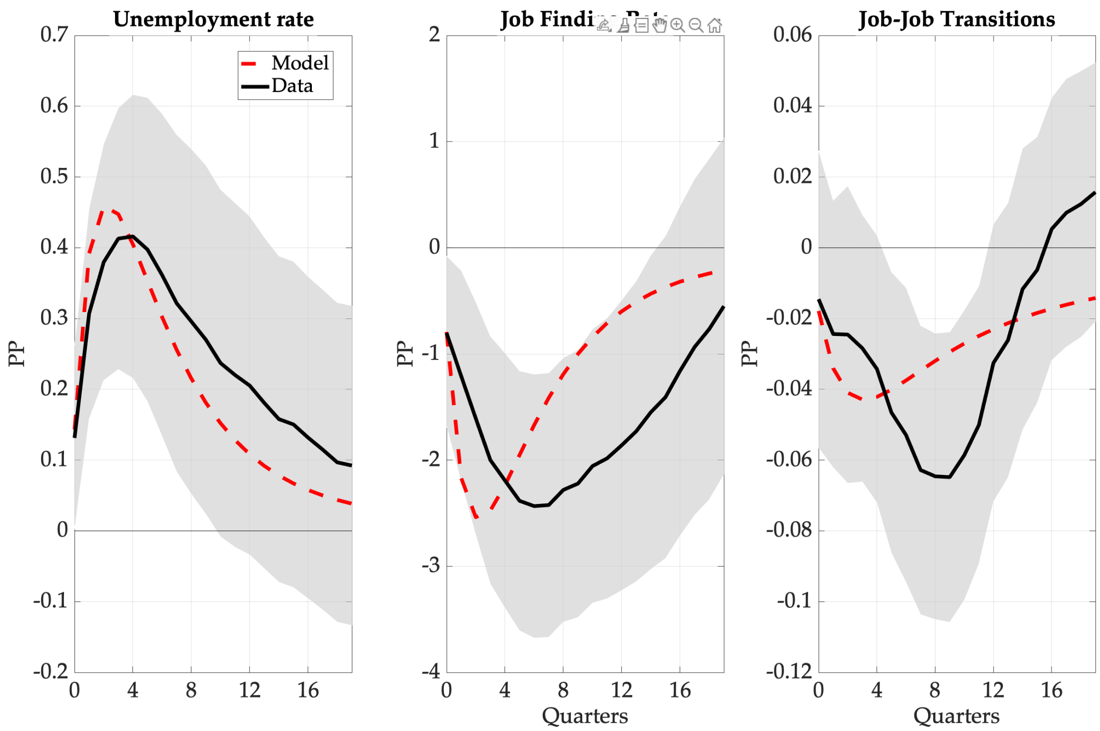
Figure 7 plots the impulse responses from the empirical exercise and the impulse responses implied by the estimated model in response to a noise shock and a persistent TFP shock. The model fit is good, with all the model-implied impulse responses falling within the confidence bands from the empirical exercise. The impact as well as the dynamics for the unemployment rate, the job-finding rate and job-to-job transitions match the empirical impulse responses well. The dynamics for vacancies and the hiring rate are not matched as well, as the model fails to capture the curvature that 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 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 the unemployment rate (U), job vacancies (V), job-to-job transitions (EE), job transitions from unemployment to employment (UE), and the 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 acknowledging that the full-information model already incorporates features like wage rigidity and on-the-job search—factors known

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.

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	0.121	-0.742	0.132	-0.768	0.151	-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 the standard deviations of key labor market variables and their correlations with output in the model. The data here have been simulated from the model and HP-filtered with smoothing parameter λ = 1,600.

to induce volatility in search models (Shimer, 2005).[19] Yet, the introduction of imperfect information augments the volatility of unemployment by an additional 18% 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 noise shocks explain about a third of the variance in labor market variables at short-run horizons. 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 an 8-quarter horizon. The benchmark model matches the forecast error variances of the key labor market outcomes observed in the data reasonably well. The model predicts that noise shocks explain 31% of the forecast error variance in the unemployment rate, which is about 90% of the corresponding share in the data. 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.

[19] In the calibration in Table 6, the full-information model generates about 75% of the observed unemployment volatility, which aligns with Gertler, Huckfeldt, and Trigari, 2020.

5 Role of Imperfect Information in Labor Market Dynamics

In this section I document that the calibrated model successfully matches the observed persistence of 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. This additional persistence is generated through two channels. First, learning under imperfect information generates endogenous persistence: agents initially under-react to productivity shocks. Together with sticky wages, this causes an initial delay in labor-market dynamics and thus increases persistence. Second, noise shocks themselves may prolong recoveries, because agents can mistake them for actual productivity shocks and adjust behavior accordingly—even though fundamentals are unchanged.

After establishing the mechanism, I present a counterfactual exercise that demonstrates how imperfect information can contribute significantly to the slow recovery of the unemployment rate during recessions, and show that the model with imperfect information can closely match the unemployment path across several postwar recoveries. Finally, I discuss the importance of other channels proposed to generate persistence in search-and-matching models, such as sticky wages and on-the-job search. I find that while sticky wages alone can generate about 45% of the observed persistence, its interaction with imperfect information accounts for about 70% of the persistence, highlighting the importance of that interaction.

5.1 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 where firms and workers can perfectly observe the persistent and transitory components of aggregate productivity each period. In an environment characterized by imperfect information, agents—both firms and workers—operate under Bayesian learning: they assign probabilistic weight to shocks being persistent, transitory, or merely noise. I find that incorporating imperfect information about shock persistence increases the persistence of unemployment by about 30% relative to the full-information model; this operates through two channels.

Channel 1. The response to a persistent productivity shock becomes more persistent under imperfect information. Consider a negative persistent shock. Initially, firms and workers attach positive probability to the shock being persistent, transitory, or noise, which induces an initial under-reaction that is amplified by wage rigidity. Sticky wages make agents reluctant to adjust wages quickly because if the shock turns out to be transitory or noise, such adjustments would be suboptimal. Relative to a full-information model, wages, vacancies, and search effort therefore decline less initially, producing an overall delay in the labor-market response.

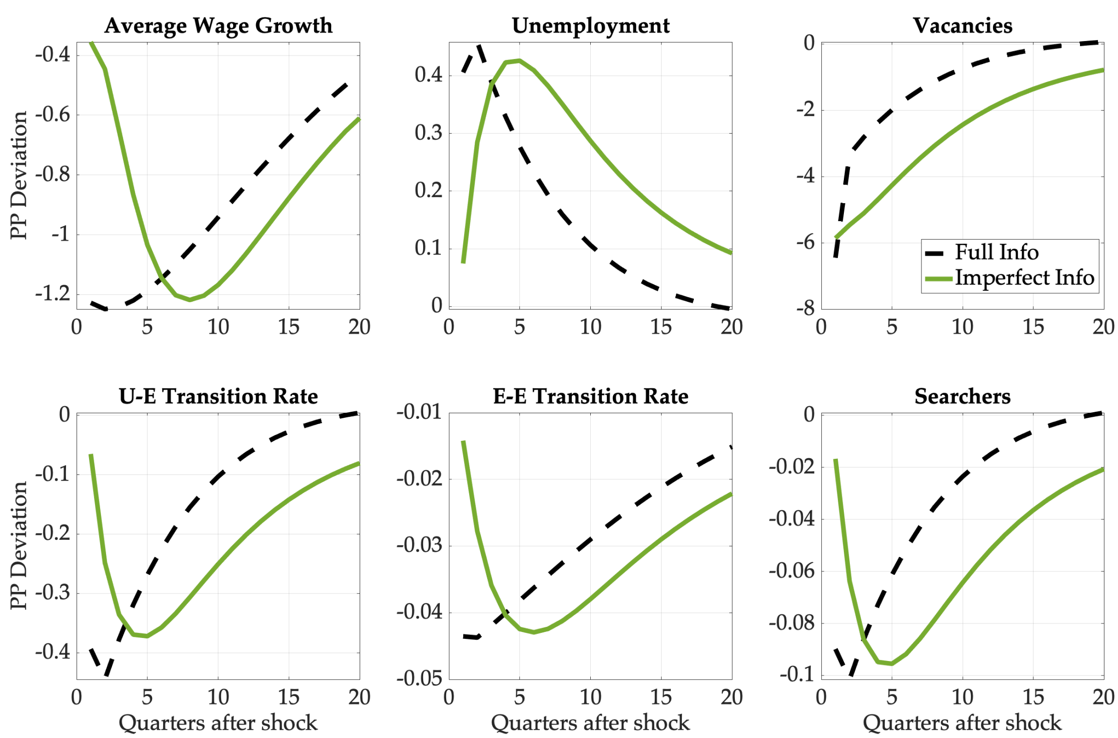
As agents update beliefs and place more weight on the shock being persistent, wages negotiated at renegotiation opportunities fall and average wages decline. Unemployed workers reduce search effort as expected returns from employment decline; employed workers reduce their upward search intensity; and firms post fewer vacancies as they expect lower returns from hiring. These forces lower matching efficiency and job-finding rates, generating a hump-shaped increase in unemployment that is more persistent than under the full-information benchmark.

This channel crucially depends on sticky wages: with fully flexible wages, adjustments would be quicker as agents learn, and recoveries would be faster. On-the-job search further amplifies this effect because employed workers occupy low-quality matches and crowd out unemployed workers; firms then post fewer vacancies, further delaying unemployed workers' job-finding.

Channel 2. Noise shocks provide an independent source of persistence. A negative noise shock leads agents to partially attribute the perceived productivity decline to an actual change in fundamentals, even though true productivity is unchanged. Firms expecting lower returns post fewer vacancies; unemployed workers reduce search intensity anticipating lower wages; employed workers cut upward search. Together these responses reduce matches and raise unemployment despite the absence of a fundamentals decline.

Both channels interact and are amplified by sticky wages and on-the-job search. When agents receive a sequence of shocks (persistent, transitory, and noise), they tend to overestimate the persistence of negative shocks in the presence of noise and behave as if facing a more persistent decline than actually occurred. Firms thus post fewer vacancies for longer, and the resulting congestion and lower search intensity slow the recovery of the unemployment rate.

Figure 8: Impulse Response to a Negative Persistent TFP Shock



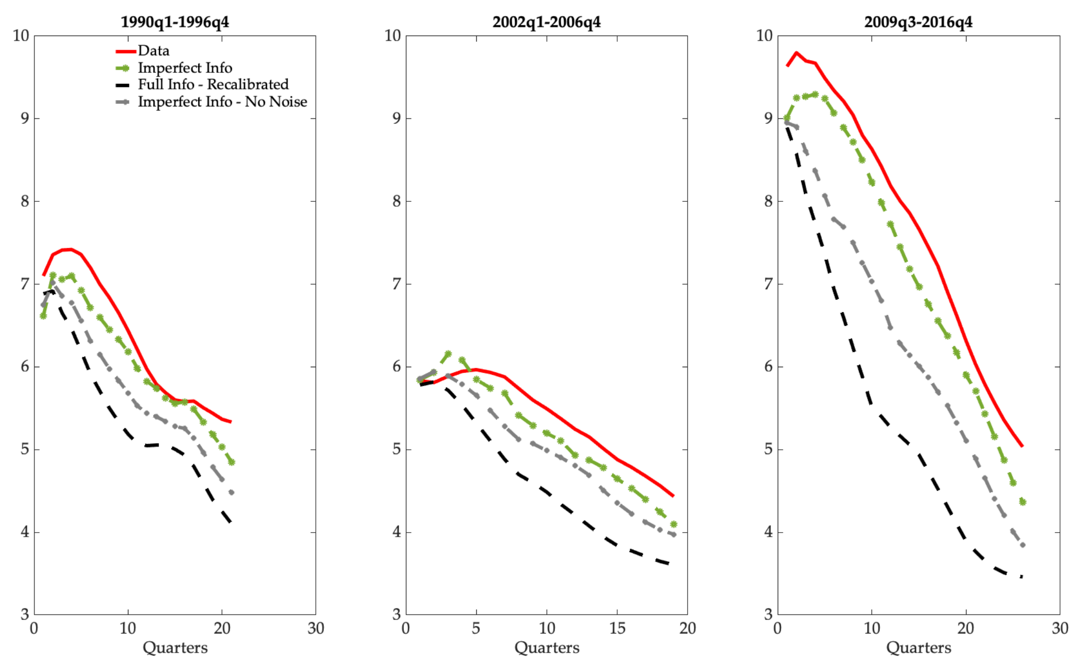
Note: This figure shows the impulse response functions for the recalibrated full-information model (dashed black line) and the imperfect-information model (solid green line) to a negative one-standard-deviation persistent TFP shock.

During downturns both channels can act together and amplify unemployment persistence. Agents tend to overestimate the persistence of negative productivity shocks in the presence of noise shocks and therefore behave as if the decline is more persistent than it actually is. As they slowly learn whether shocks are persistent or transitory, firms and workers initially respond as if facing a larger, persistent negative shock. Firms thus expect lower future revenue and post fewer vacancies for longer than warranted by fundamentals. The decline in vacancies reduces job-offer arrival rates for both the unemployed and the employed, who lower their search effort as the returns to search fall. Because many bad matches remain occupied and good jobs are scarce, congestion at the lower rungs of the ladder further depresses unemployed workers' job-finding rates, keeping unemployment elevated longer than implied by fundamentals.

5.2 Unemployment Dynamics across Recessions: Data vs Model

In this section I simulate the calibrated imperfect-information model to generate counterfactual unemployment series for five recessions between 1970 and 2019. This exercise shows that imperfect information helps explain the slow recovery of unemployment, especially in the last three recessions. For each exercise the model is normalized to match the starting unemployment rate. When simulating the imperfect-information model with noise, all three shocks identified in the VAR act each period; the imperfect-information model without noise uses only the persistent and transitory shocks. For the full-information model I introduce the persistent and transitory shocks each period and recalibrate the model (as described above) to match empirical IRFs to persistent shocks. Estimated parameters for the full-information model appear in the Appendix.

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



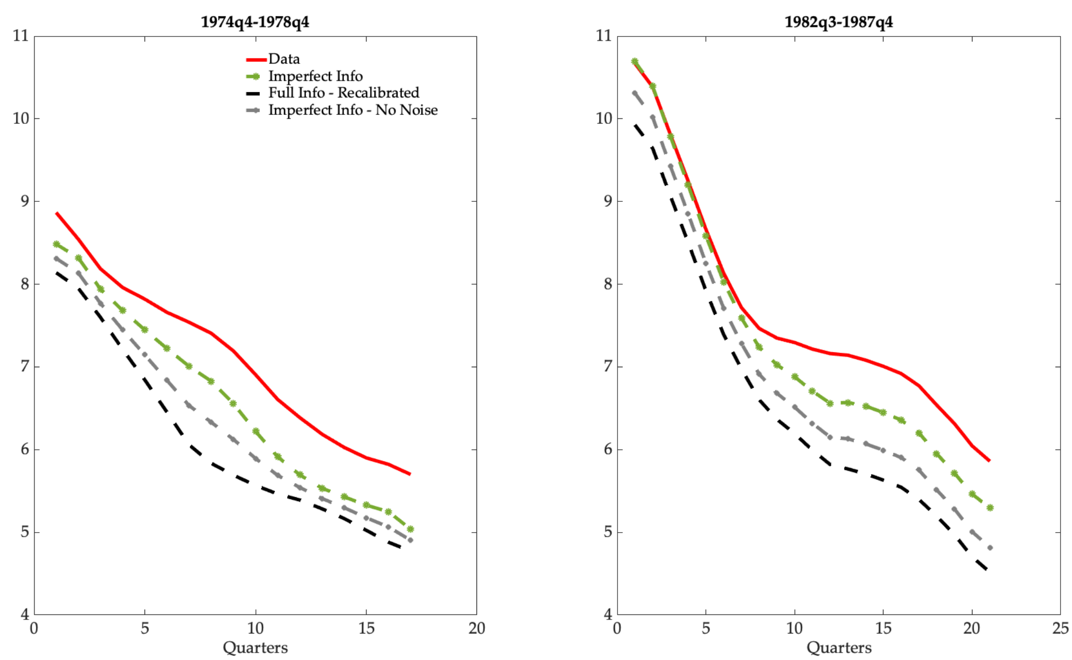
Note: This figure shows model-implied simulated unemployment for the recalibrated full-information model (dashed blue), the imperfect-information model without noise (gray), and the imperfect-information model with noise (solid green) for the Great Recession, the 2001 recession, and the 1990–91 recession.

The imperfect-information model captures the persistence of unemployment well for the three recessions after 1990. In contrast, the full-information model predicts much faster recoveries. For the Great Recession, the unemployment rate took 37 quarters to return to its pre-recession trough; the imperfect-information model predicts 32 quarters, while the full-information model predicts 24 quarters (about 33% faster than the imperfect-information prediction).

For the 2001 recession the data show a 24-quarter recovery; the imperfect-information model predicts 20 quarters and the full-information model 16 quarters. In the 1990–91 recession the data show 28 quarters; the imperfect-information model predicts 22 quarters while the full-information model predicts 16 quarters. These differences underscore the contribution of imperfect information: larger noise shocks make agents perceive negative productivity shocks as more persistent than they are, and slow learning combined with sticky wages produces slower recoveries.

For pre-1990 recessions the full-information and the two imperfect-information models give similar predictions because the noise shocks identified in the SVAR play a smaller role. With smaller noise shocks, agents' perceived productivity is closer to true productivity and recoveries are similar across models. For example, in the 1981–82 recession (14 quarters), the imperfect-information model with noise predicts recovery in 11 quarters while the full-information model predicts 9 quarters. In the 1973–78 recession (23 quarters), the imperfect-information model with noise predicts 17 quarters while the full-information model predicts 14 quarters. Results are summarized in Appendix Table B2.

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



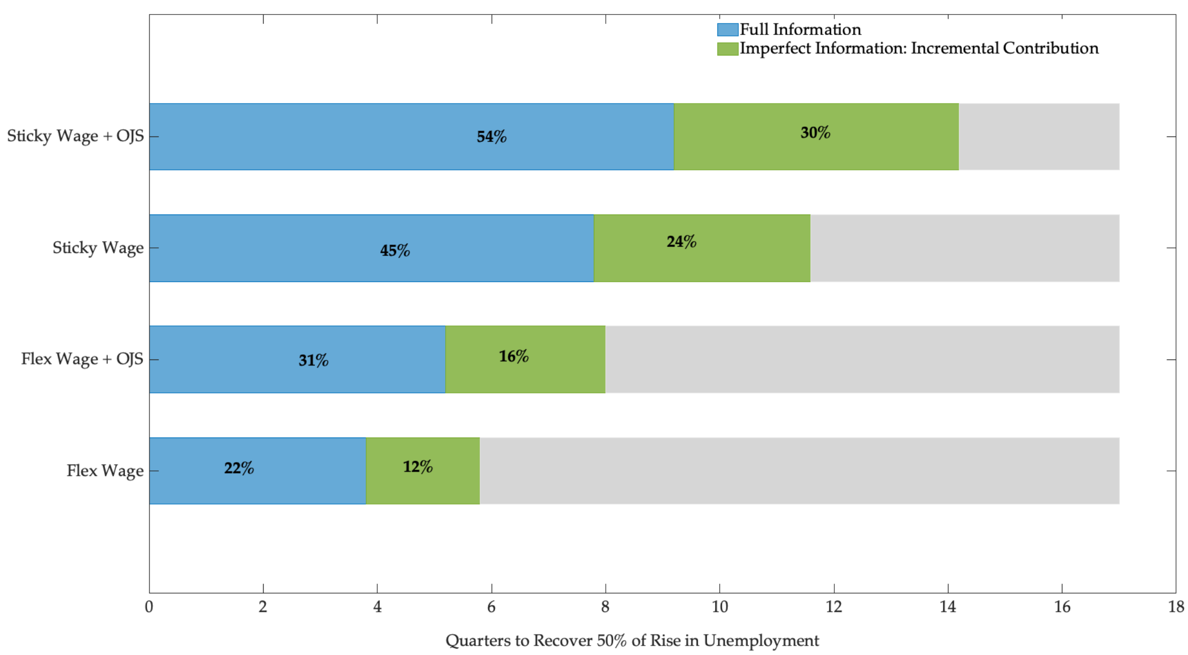
Note: This figure shows model-implied simulated unemployment for the recalibrated full-information model (dashed blue), the imperfect-information model without noise (gray), and the imperfect-information model with noise (solid green) for several pre-1990 recessions.

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

In this section I compare unemployment persistence across mechanisms with and without imperfect information. The model contains three sources of persistence: on-the-job search, sticky wages, and learning. To quantify each channel, I compare a full-information benchmark to the imperfect-information model under four 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 persistence measure is the average number of quarters across recessions required to recover 50% of the rise in unemployment (see Equation 1). For each recession between 1968 and 2019 I compute the share of the recessionary rise in unemployment that is reversed during the subsequent expansion, and record the number of quarters until a 50% recovery is achieved. Empirically this average is 17 quarters. To show how learning contributes under each specification I plot this measure in Figure 11. In the stacked bar graph I recalibrate the full-information model as described in Section B.2.

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



Note: This figure shows the model-implied average duration (quarters) to recover 50% of the rise in unemployment from recession start, averaged across recessions between 1968 and 2019 for various model specifications. Percentages indicate the share of the empirical duration (18 quarters) explained by each specification. The green segments show the incremental contribution of learning; the total imperfect-information contribution is the sum of the blue and green bars.

Role of sticky wages. Sticky wages generate persistence by making downward wage adjustment sluggish. When wages adjust slowly during recessions, firms' incentives to hire remain low, hiring falls, and job-finding rates stay depressed longer than under flexible wages. Introducing sticky wages without on-the-job search accounts for about 45% (≈7 quarters) of the 50% recovery duration under the full-information benchmark.

Role of on-the-job search. On-the-job search produces congestion: during downturns more employed workers remain in bad matches and unemployed workers have fewer low-productivity vacancies to move into. Employed workers also search less intensively, which leads firms to post fewer vacancies and further reduces unemployed workers' job-finding probabilities. In a flexible-wage full-information model, introducing on-the-job search explains about 30% (≈5 quarters) of the recovery duration; with sticky wages the full-information model predicts about 54% (≈9 quarters).

Role of imperfect information. The previous two paragraphs show that on-the-job search and sticky wages already produce considerable persistence—together they predict a 50% recovery in about 10 quarters under the full-information benchmark. To quantify imperfect information's added effect, consider that during downturns noise shocks make agents perceive productivity shocks as more persistent than they are. Because agents learn only gradually whether a shock is persistent or transitory, they behave as if facing a more persistent negative shock for several periods. Firms lower hiring and workers reduce search effort, reducing matches until learning occurs. Adding imperfect information to the flexible-wage, no-on-the-job-search case increases persistence, predicting a 50% recovery in about 6 quarters (≈35% of the total).

Learning interacting with on-the-job search adds roughly another 16% to persistence, yielding a 50% recovery in about 8 quarters. Employed workers learn slowly and continue to expect worse productivity, so their search effort remains dampened; firms post fewer vacancies, and unemployed workers' job-finding probabilities remain lower for longer.

Learning interacting with sticky wages raises persistence even without on-the-job search. Firms anticipating persistently lower productivity reduce hiring, and slow wage adjustments further dampen hiring incentives. Workers cut search effort, and together these forces depress job-finding rates for longer. Imperfect information with sticky wages predicts an 11-quarter horizon to recover 50% (≈65% of the empirical duration), about 24% longer than the sticky-wage full-information model.

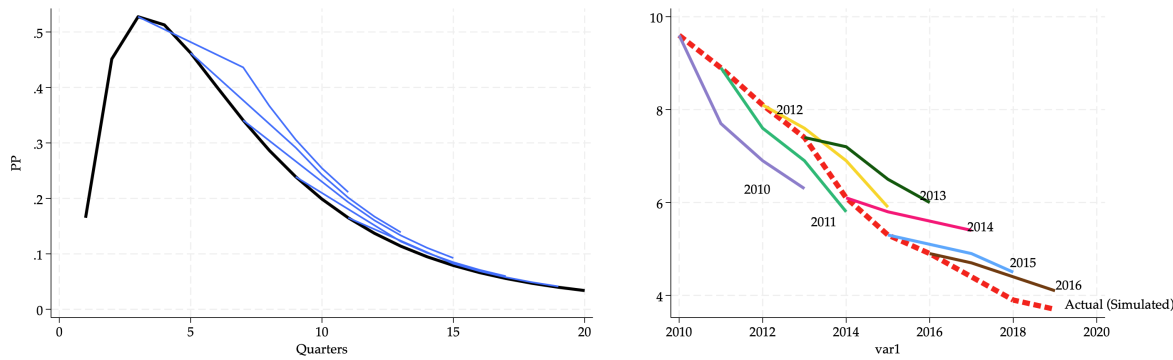
Finally, imperfect information combined with sticky wages and on-the-job search adds about 5.5 quarters (≈30%) to the average duration to recover 50% relative to the full-information counterpart. In equilibrium, agents' anticipation of persistently lower productivity depresses hiring and search; sticky wages and reduced on-the-job search amplify these effects, jointly generating roughly 84% of the observed persistence.

In Appendix Section B.5.2 I present a decomposition comparing the full-information model with the imperfect-information model without noise shocks. That analysis shows that learning alone increases unemployment persistence even without noise shocks: in the sticky-wage, on-the-job-search model imperfect information adds about 18% (≈3 quarters) to persistence. This underscores the importance of incorporating imperfect information in search-and-matching models to better predict recovery durations.

5.2.2 Unemployment Forecasts in the Model.

The model implies distinctive forecast dynamics. Under a persistent productivity shock agents under imperfect information attribute part of the shock to noise or the transitory component, causing their projections to under-react to the actual rise in unemployment. Conversely, under a noise shock agents may attribute some of it to a persistent or transitory productivity decline and initially forecast unemployment to be higher than it will be; as they learn that the shock is noise, forecasts converge to the realized unemployment path. Figure 12 illustrates this: Panel (a) shows 4–8-quarter-ahead forecasts in response to a noise shock together with the impulse response of unemployment; Panel (b) shows actual and forecasted unemployment in response to a persistent TFP shock.

Figure 12: Long-Run Unemployment Projections in the Model



(a) Response of Unemployment to a Noise Shock

(b) Unemployment Projections: Great Recession

Note: Panel (a) shows model-implied 4–8-quarter-ahead projections in response to a noise shock; the solid thick black line is the actual unemployment response. Panel (b) shows model-implied one-, two-, and three-year-ahead forecasts for the Great Recession. While simulating, all three VAR-identified shocks act each period.

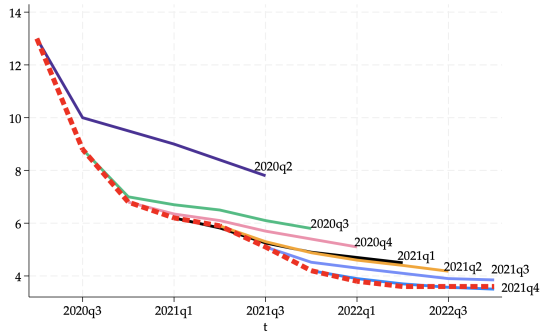
To show that noise shocks can reproduce the over-shooting of unemployment projections observed in the data, I simulate long-run forecasts after the Great Recession. When the persistent shock contribution dominates, projections under-react; when the noise contribution dominates, projections over-estimate unemployment. The historical decomposition in Figure A11 indicates that noise shocks' contribution to unemployment movements rises after 2012. In the model this generates initial under-estimation when persistent shocks dominate and later over-estimation as noise becomes more important—mirroring the pattern in the data (Figure 2b). Note that noise shocks are unique in producing long-run over-estimation; for other structural shocks long-run expectations tend to under-estimate unemployment.

5.2.3 Unemployment Dynamics during COVID-19 Recession

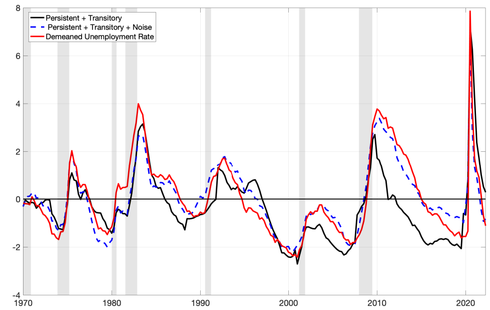
Finally, I consider the COVID-19 recession, which features one of the fastest recoveries on record. Unemployment rose from 3.5% in February 2020 to 14.7% and then declined to 3.9% by end-2021; much of the rise reflected temporary layoffs. Unemployment from temporary layoffs typically falls quickly as activity recovers because workers can return to their jobs once demand improves. To assess imperfect information I examine short-horizon (1–4 quarter) forecasts from the Survey of Professional Forecasters (Figure 13a) and longer-horizon (1–3 year) forecasts (Figure A2b). Forecasters revised short-horizon expectations rapidly by 2021 Q4 and longer-horizon projections by 2021, indicating they treated this recession as relatively transitory. In our framework, this implies noise shocks played a smaller role during COVID-19.

To be explicit, I extend the SVAR to include the pandemic (sample 1968–2022). Max-share identification still targets the shock that maximizes TFP forecast-error variance at long horizons; given the pandemic's recent occurrence I also consider short-horizon FEV maximization. Identification of noise

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.

shocks does not depend on max-share, so the exercise remains informative about noise-driven dynamics. Figure 13b shows that noise shocks did not play a major role in this recession: most variation is captured by TFP shocks. This aligns with rapidly adjusted expectations and a swift recovery, implying that misperception was smaller than in recessions such as 2007–09 and that fundamentals accounted for most of the rise and the quick recovery.

6 Conclusion

This paper assesses 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 six quarters 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 and on-the-job search. This is particularly true for the period after 1990, emphasizing the increased importance of imperfect-information in more recent economic conditions. In conclusion, it is important for models of business cycles in the labor market to consider the role of noise shocks.

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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.

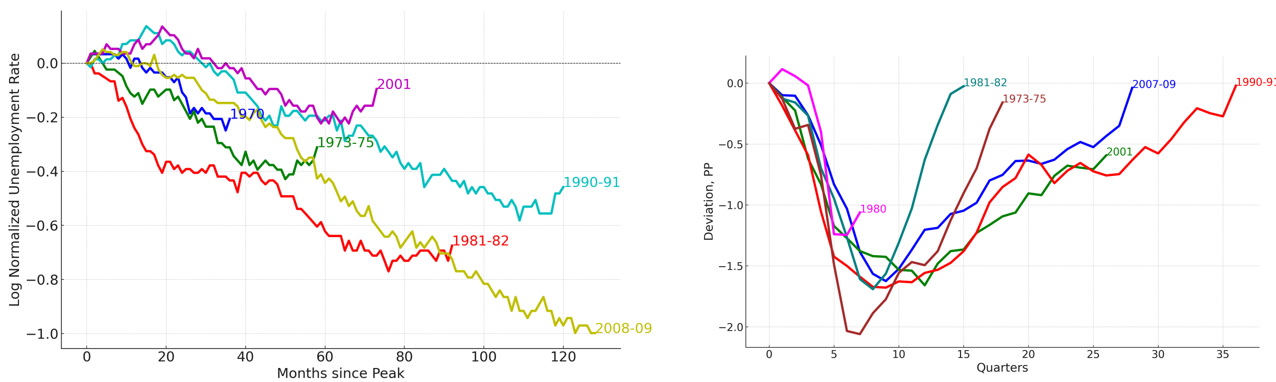
5. Aggregate productivity is measured as the Solow residual, for which I rely on the utility adjusted series from Fernald, 2014, also updated by the Federal Reserve Bank of San Francisco.

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

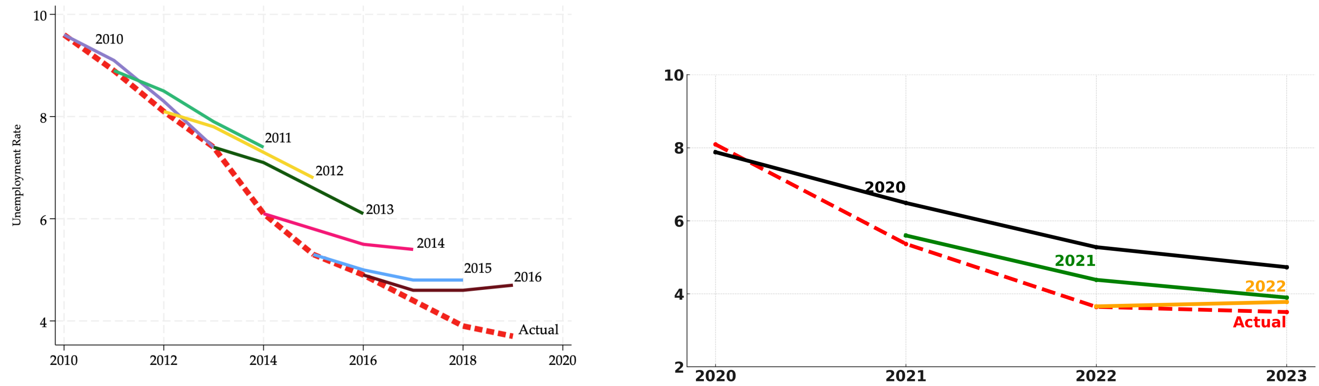
A.3 Projections from Forecasters and Policymakers

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. 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.

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



(a) Projections: Great Recession

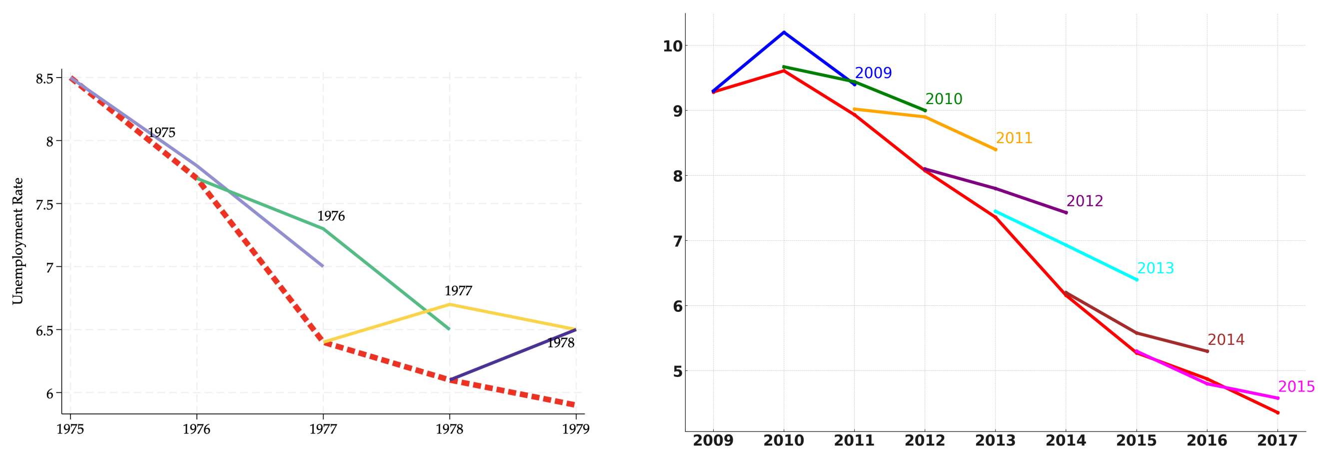
(b) Projections: Covid-19

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

Livingston Survey The Livingston survey is the longest running survey of forecasters starting in 1946.[20] 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.

Figure A3: Projected Unemployment Rate from the Livingston Survey



(a) 1973-74 Recession

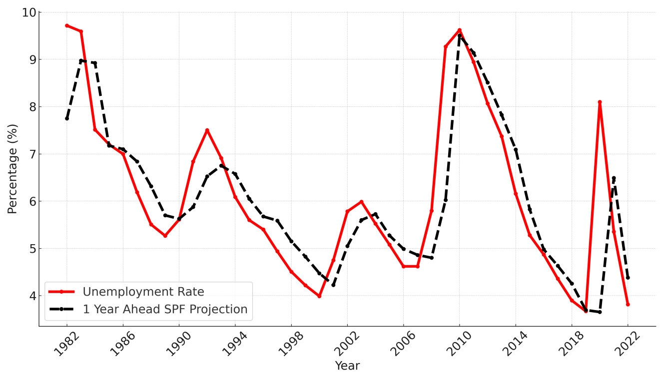
(b) 2009-07 Recession

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

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

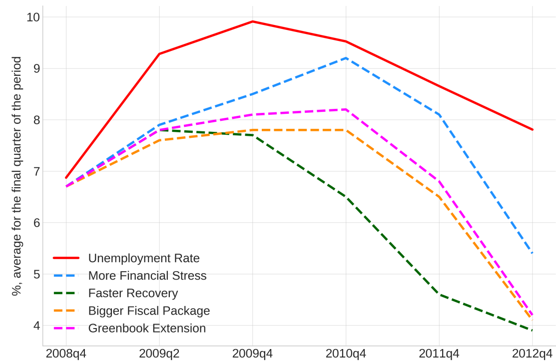
Policymakers. Now, to illustrate that it can be challenging even for policymakers to correctly assess the nature of the recession, I present the projections from Federal Reserve's Greenbook in December 2008 in Figure A4b. Under all scenarios, the Federal Reserve Board predicted a much faster recovery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

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

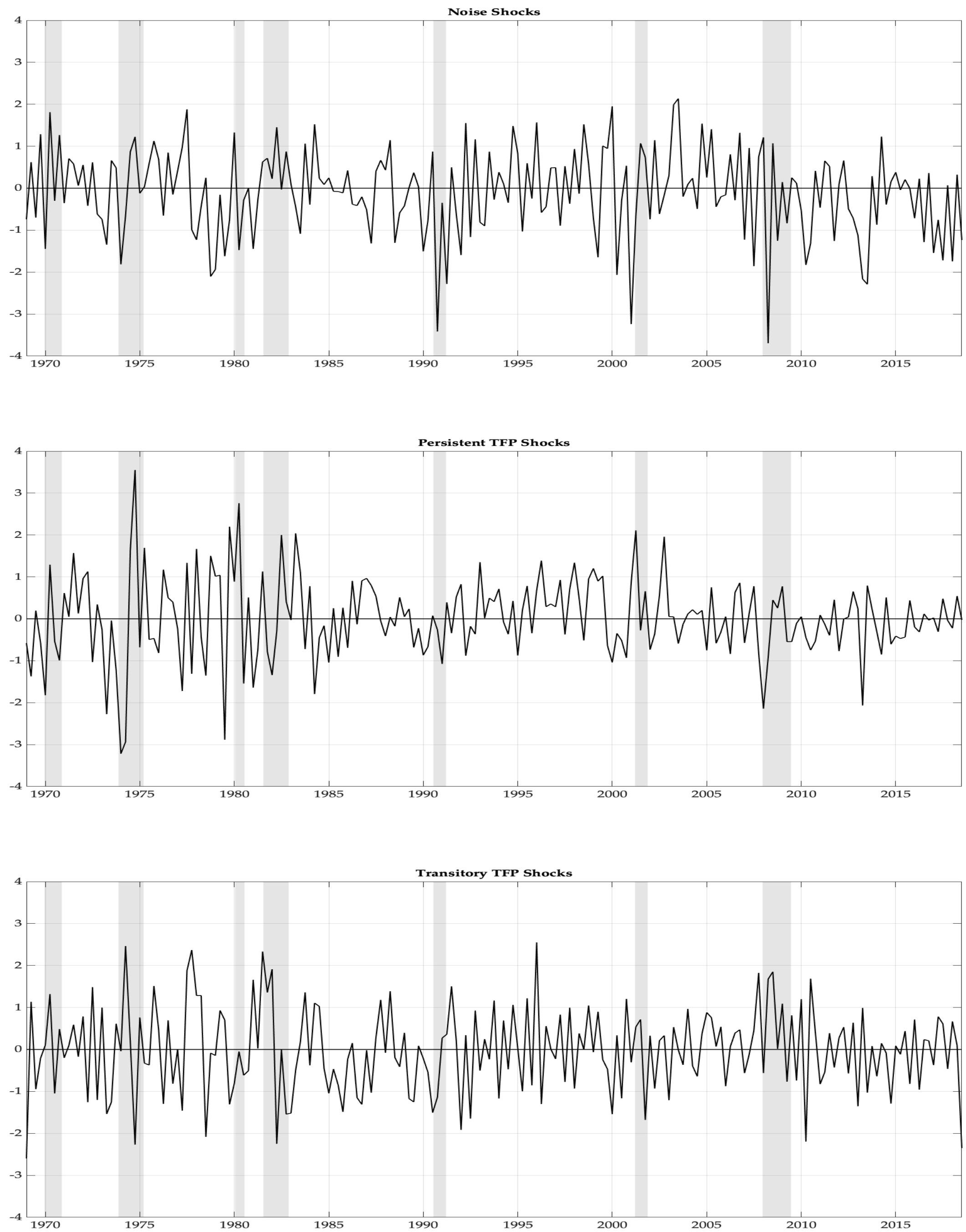


Note: Panel (a): The black dashed line represents the median 1 year ahead projection of unemployment rate from the Survey of Professional Forecasters. The solid red line is the actual unemployment rate. Panel (b): The black dashed line represents the projection of unemployment rate from the December 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.

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.

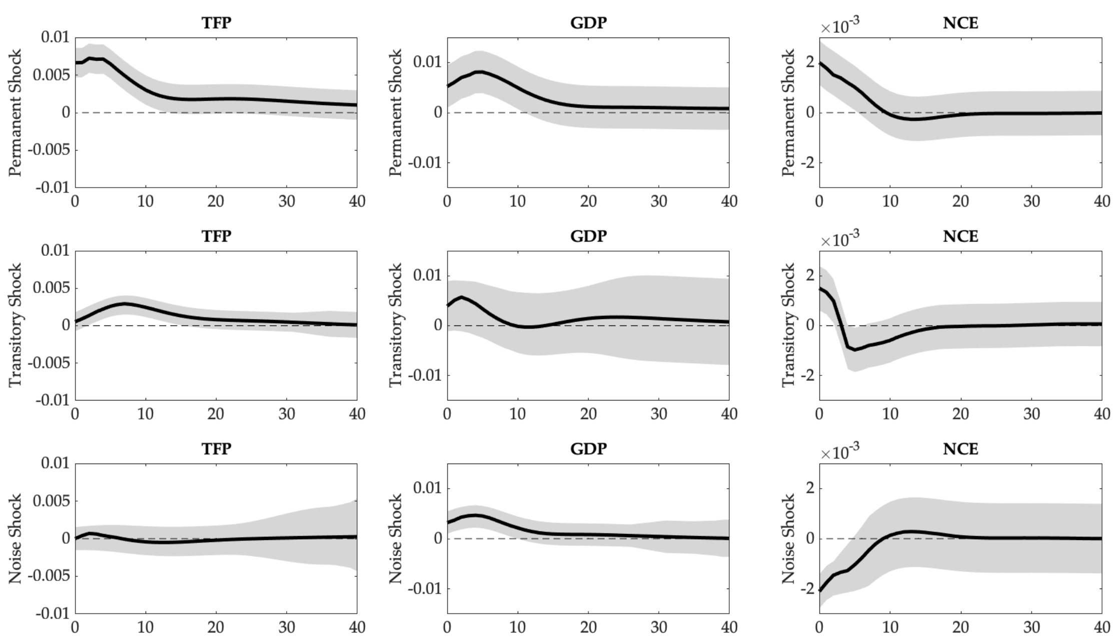
VAR Impulse Response Functions. The VAR's impulse responses, illustrated in Figure A6, align with both the model's stipulated assumptions and economic reasoning. Specifically:

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

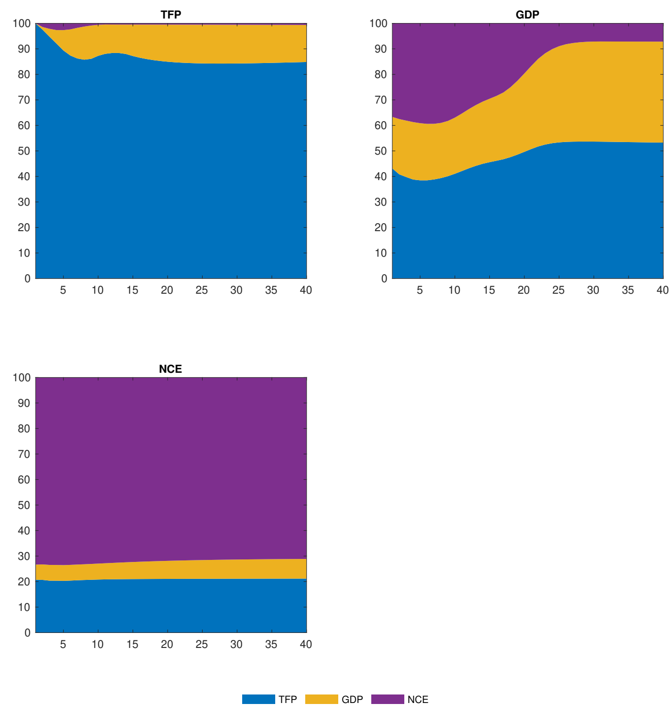
Figure A6: Impulse Response from the VAR



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:

$$y_{t+h} = \alpha^j_h + \beta^j_h u^j_t + \sum_{p=1}^{P} \gamma^j_p \omega_{t-p} + \mu^j_{h,t+h} \tag{39}$$

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

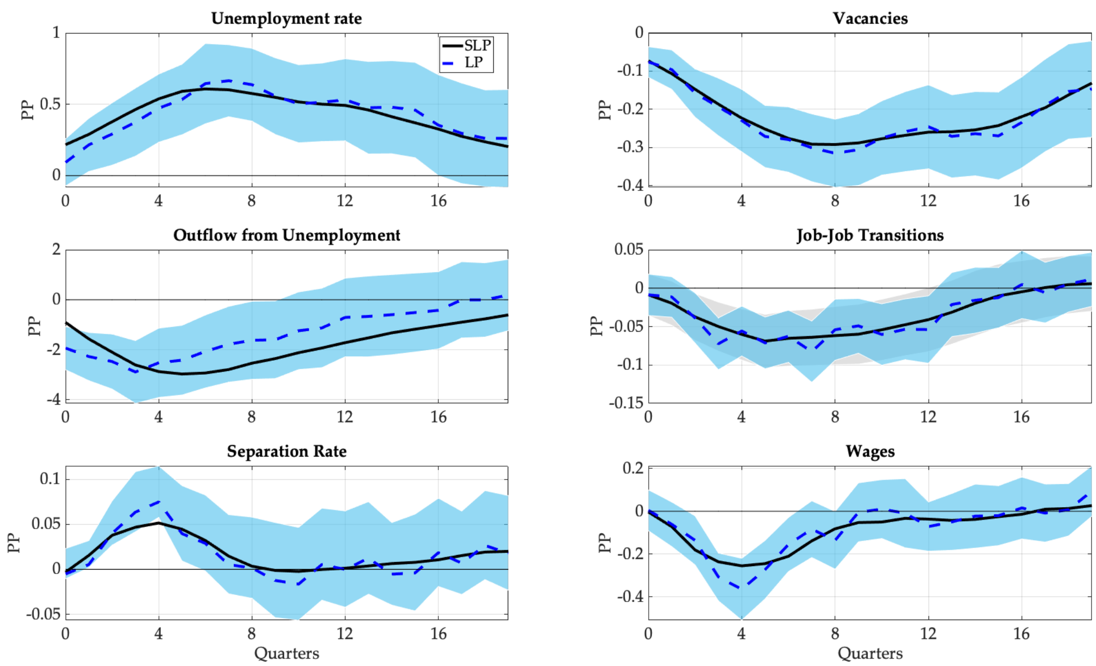
Following Barnichon and Brownlees, 2019, one can approximate $\beta^j_h \approx \sum_{k=1}^{K} b^j_k B^j_k(h)$ using a linear B-splines basis function expansion in the forecast horizon h. Thus, the corresponding smooth Linear

Projections can be written as Equation 40.

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

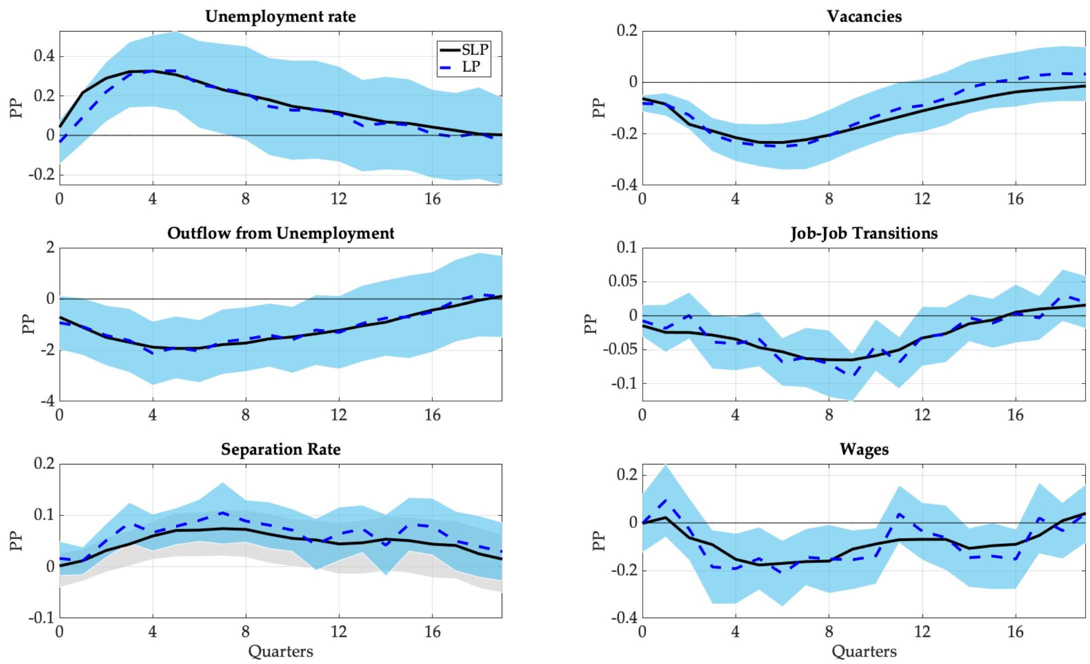
The SLP is estimated using generalized ridge estimation. When the shrinkage parameter is small, it is close to the least square estimation and has zero bias but potentially large variance.When the shrinkage parameter is large, the estimator is biased but has smaller variance than the least squares estimator. 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

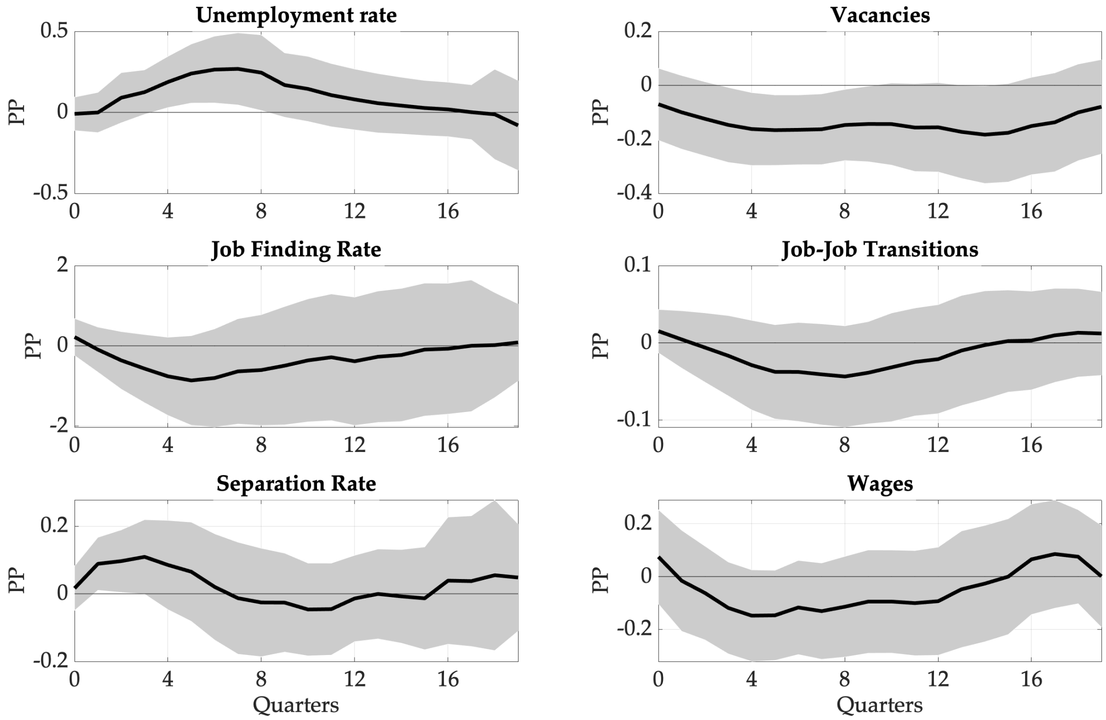
To understand the role of imperfect information over the business cycle, it is useful to understand how much of the deviation of the key labor market outcomes from their predicted path can be explained by the productivity shocks. If noise shocks are not important, the productivity shocks would explain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

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

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

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



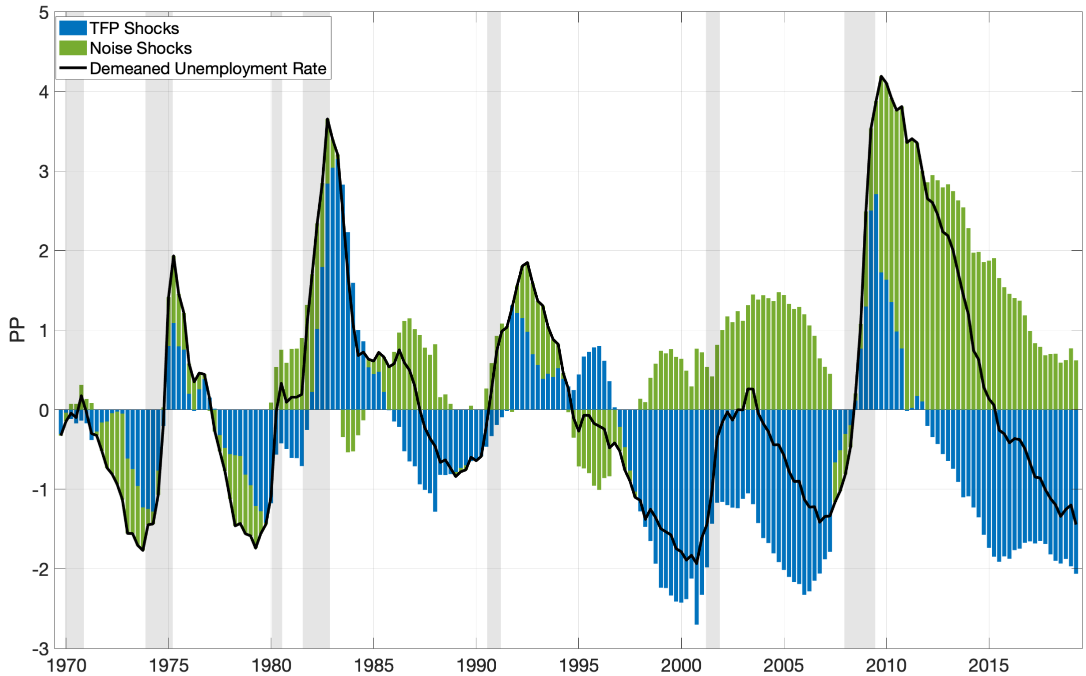
Note: This figure plots the impulse response functions for key labor market variables to a transitory TFP shock. The shaded area represents a 95% confidence interval.

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

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

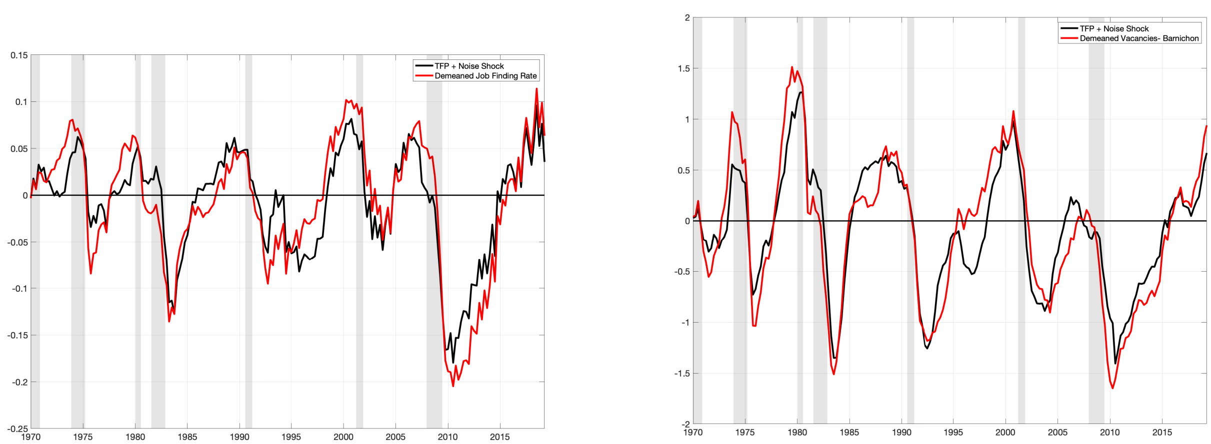
In Figure A11, I present the contribution of the two TFP shocks (in blue) and the noise shocks (in green) in the VAR to the movements in unemployment rate. The noise shocks contribute significantly to the unemployment rate during the recessions in 1990-91, 2001 and 2007-09. In Figure A12 I plot the cumulative 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

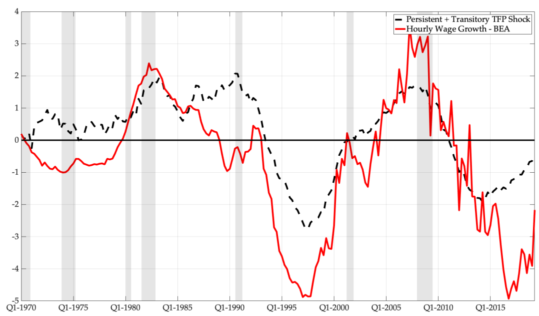


(a) Job Finding Rate

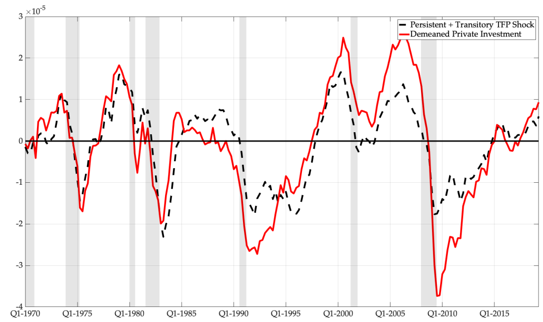
(b) Vacancy Posting

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 32% of this recovery across recessions.

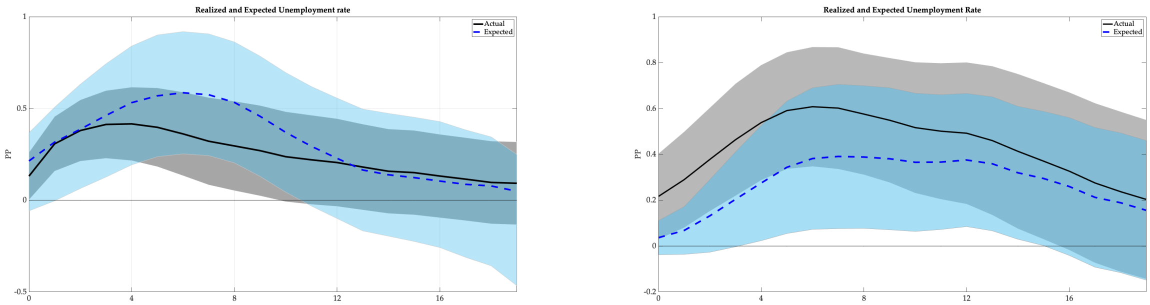
Table A1: Contribution of Noise Shocks to Recovery of Unemployment Across Recessions

	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

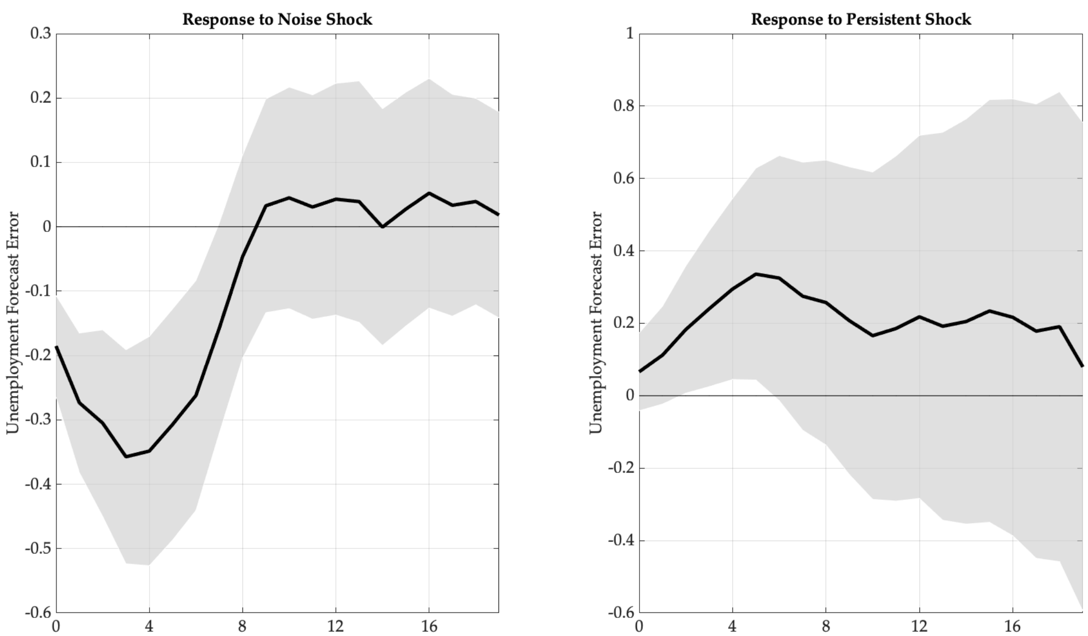


(a) Unemployment Projections: Noise Shocks

(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.

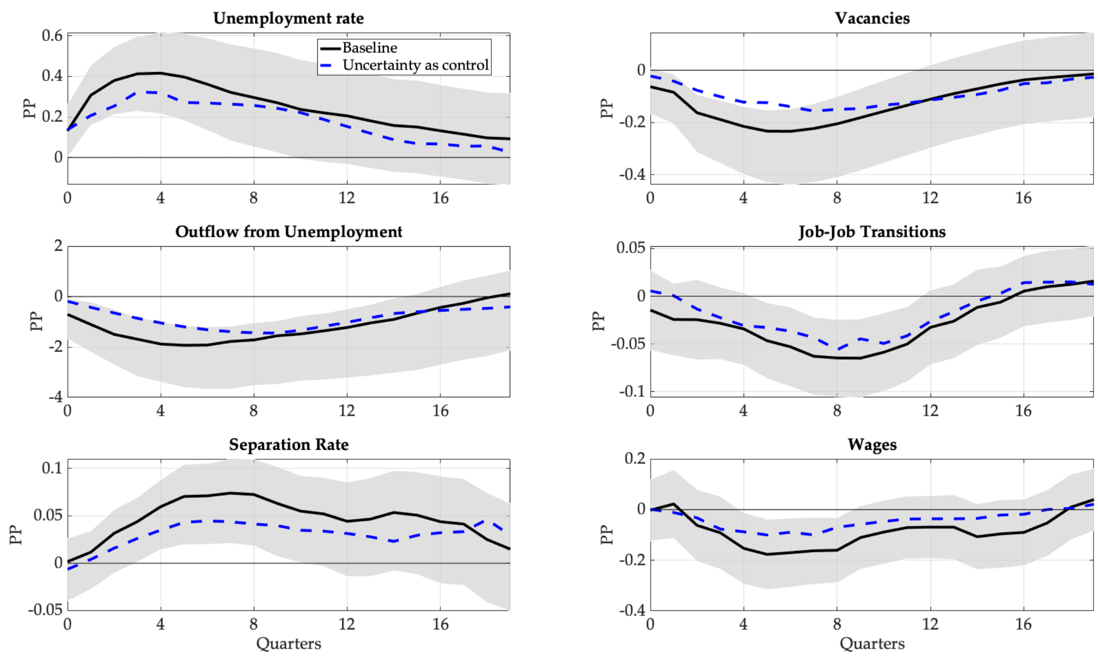
Fundamental shocks do not satisfy the sign restrictions used to identify the noise shocks, as any fundamental shock has a higher impact on actual output than expected, thus violating the sign restrictions. However, there might be some cases where uncertainty shocks might behave like the noise shocks: 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.

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

where $\tilde{\omega}_{t-p}^{j}$ 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:

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

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

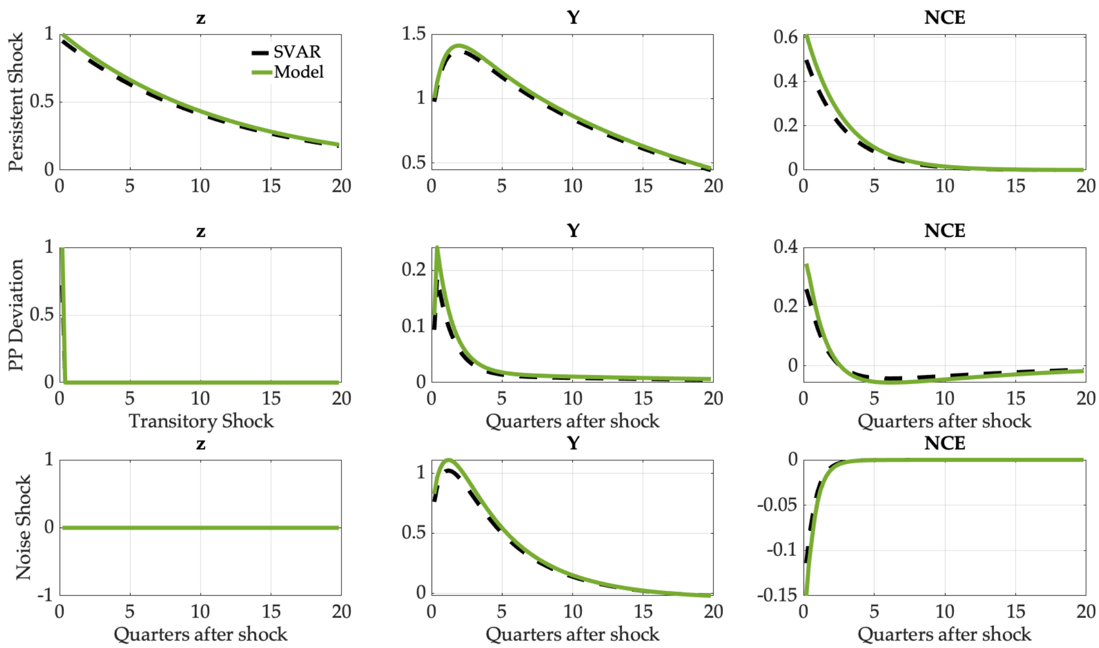
Parameters	Interpretation	Value	Target
Ψ	Match efficiency	0.48	Unemployment Rate = 0.055
κ	Cost of hiring	8.23	$U - E = 0.28$
μ	Scale parameter of search cost	0.082	$E - E = 0.025$
$1 - \sigma$	Separation rate	0.010	$E - U = 0.010$
ϕ	SS productivity from bad job	0.68	Δ Wage of E-E = 0.045
Parameters	**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

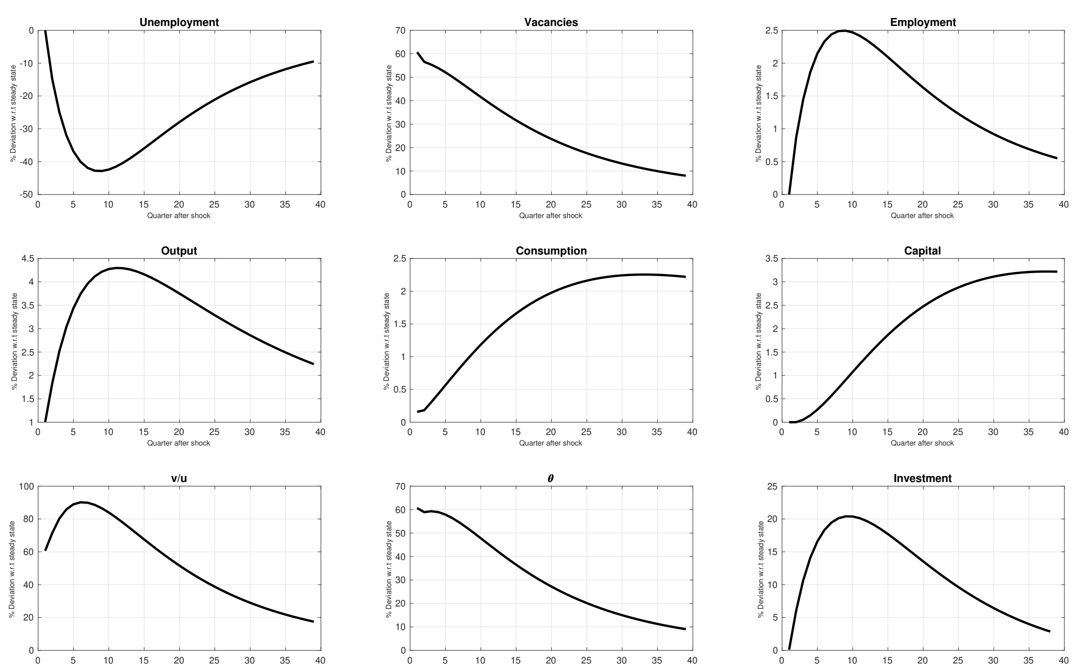
B.4.1 Impulse Responses From the Model

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

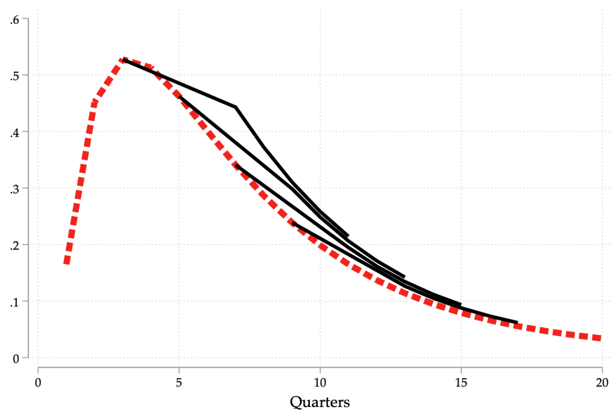


Note: This figure plots the model implied, impulse response functions to a persistent productivity shock.

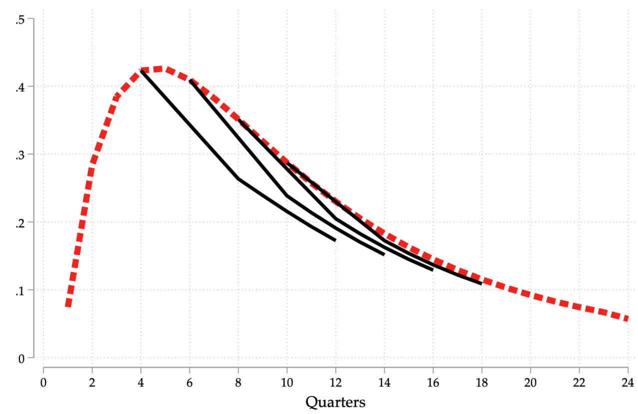
B.5 Projections from the Model

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

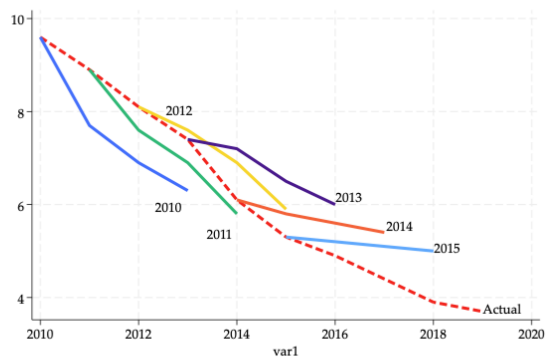


(b) Persistent Productivity Shock

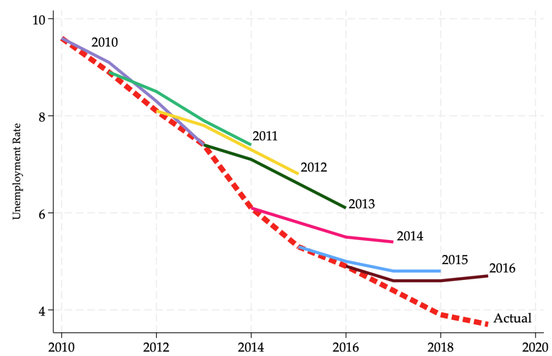
Note: This figure shows the 4-8 quarters ahead projections by the agents in the model in response to a response to a noise shock (a) and a persistent TFP shock (b). The solid thick black line is the actual response of unemployment due to these shocks respectively.

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 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.

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



(a) Unemployment Projections: Model



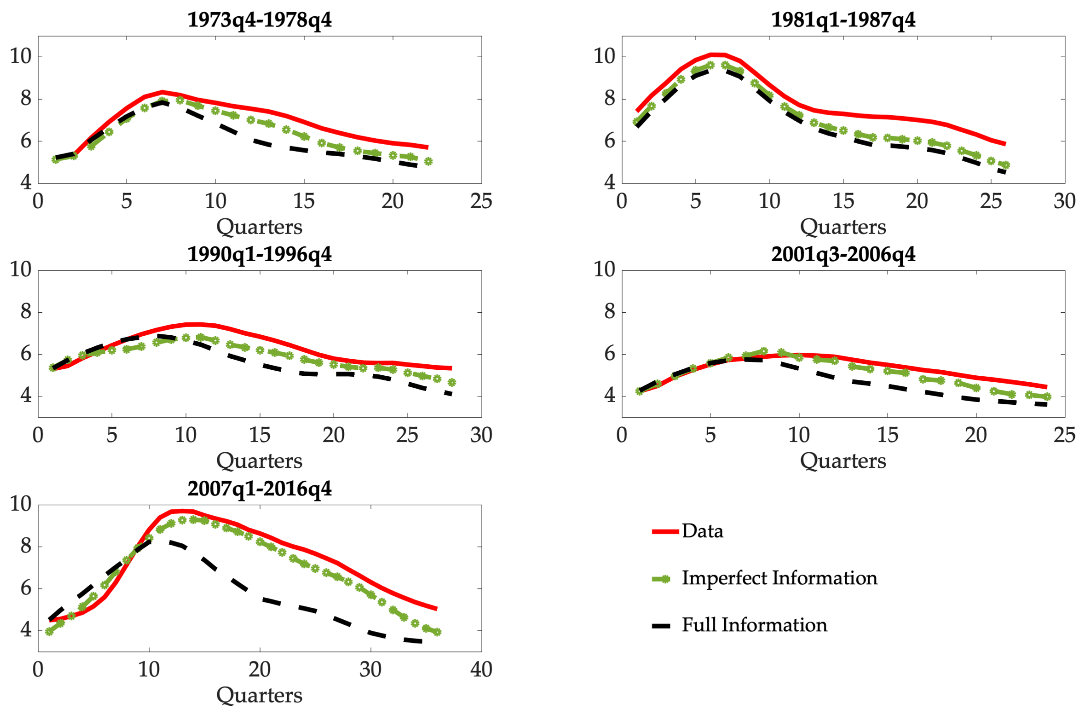
(b) Unemployment Projections: Data

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

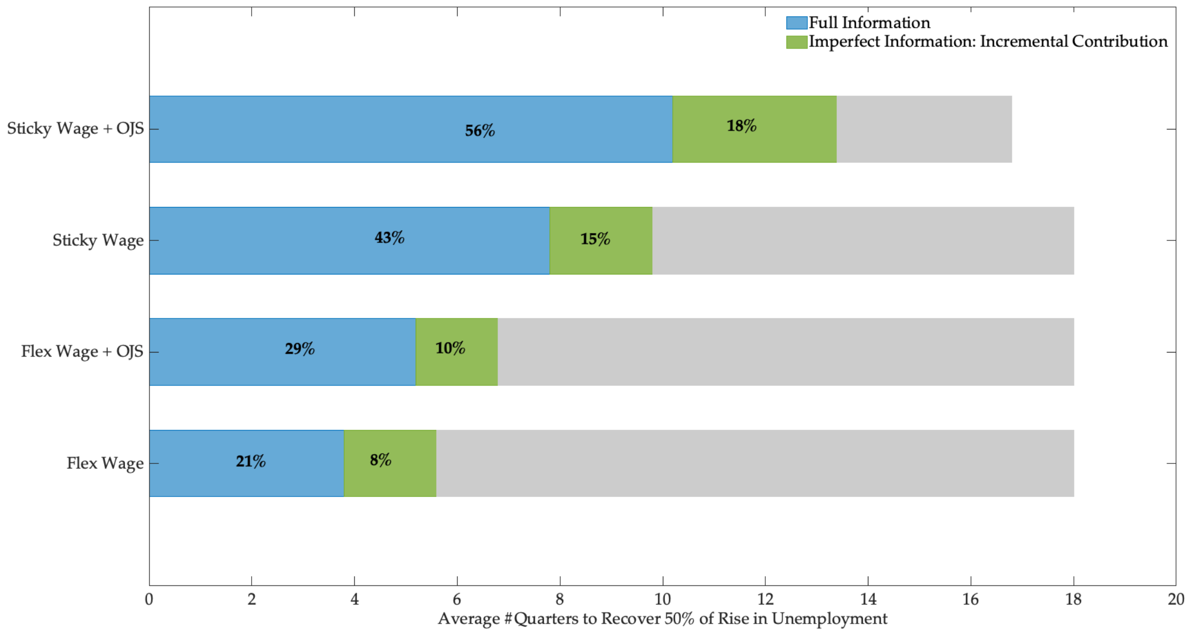
In this section, I compare the persistence and volatility of unemployment under various mechanisms with and without imperfect information. I compare the model under 4 scenarios: a) flexible wages without on-the-job search (OJS), b) flexible wages with OJS, c) sticky wages without OJS, and d) sticky wages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

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.

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.

Business Cycle Statistics Across Specifications 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	0.121	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).