Anticipated Productivity and the Labor Market*

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Abstract

We identify the main shock driving fluctuations in long-horizon productivity expectations, consistent with theories of TFP news. The identified shock induces strong comovement patterns in output, consumption, investment, employment, and stock prices even though TFP does not change significantly for more than two years. A labor search model in which wages are determined by a cash-flow sharing rule, rather than the present value of match surplus, matches the observed responses to the news shock. The model also matches the empirical patterns of vacancies, labor force participation, job-finding rates, and unemployment. The proposed wage rule is consistent with empirical responses of wages to both anticipated and unanticipated productivity changes.

Keywords: News Shocks, Wages, Labor Search, Business Cycles
JEL Classification: E32, E24

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1 Introduction

Over the last two decades, macroeconomists have become increasingly skeptical that technology could be the primary driver of business-cycle fluctuations, particularly in the labor market. From a theoretical perspective, this skepticism is rooted in the critique of Shimer (2005) that theories of flexibly-bargained wages cannot generate sufficiently large fluctuations in vacancy posting and therefore in employment. Authors have since proposed numerous theoretical resolutions to this difficulty (Hall, 2005; Hagedorn and Manovskii, 2008; Hall and Milgrom, 2008), but these proposals face empirical challenges, both from controversy surrounding the patterns of real wages in practice (see discussion below) and from the more basic observation that fluctuations in the labor market do not seem to coincide with contemporaneous measures of productivity (Angeletos et al., 2020).

In this paper, we ask whether anticipated changes in productivity could be a major driver of labor market fluctuations. Previous authors who have studied this question have come to conflicting conclusions. For example, Beaudry and Portier (2006); Portier (2015); and Bouakez et al. (2019) find evidence to support this hypothesis, while Barsky and Sims (2011); Barsky et al. (2015); and Kurmann and Sims (2020) come to more pessimistic conclusions. We first revisit this question empirically, using a structural vector autoregression to identify anticipated productivity shocks, or "news," as those explaining changes in productivity expectations *at least* 20 quarters in the future. Our approach to identification addresses the measurement error concerns raised by Bouakez et al. (2019) and Kurmann and Sims (2020), while mitigating the confounding effects that can result from shorter-run productivity surprises, as emphasized by Portier (2015) and other authors.

The shock we identify drives significant business cycle fluctuations in standard macroeconomic quantities, including more than half of employment, but only small fluctuations in inflation and statistically insignificant fluctuations in contemporaneous TFP. At horizons beyond the typical business cycle, however, we find the shock is associated with a strong and extremely persistent increase in productivity: Our identified shock strongly resembles the "technological diffusion news" described by Portier (2015). Our empirical results regarding the importance of anticipated productivity are robust to a wide range of specifications of the empirical VAR, including different lag lengths, VECM estimation with one or more trends, and including additional variables in our VAR.

Our empirical findings above are hard to reconcile with the effects of news in either standard neoclassical or New Keynesian models. Most neoclassical models would imply that labor supply should contract in response to good news about the future, while New Keynesian models could deliver an immediate expansion only in the context of increased inflation. Labor market frictions, which make labor behave more like an investment good (Hall, 2017), offer one possible response to these challenges. Accordingly, we next ask whether a standard search and matching model of the labor market can match the observed responses of business-cycle quantities to a TFP news shock of the type suggested by our data. To answer this question, we perform an impulse response matching estimation, matching a theoretical model with search and matching frictions in the labor market and Greenwood et al. (1988) preferences to our identified impulse responses.

A distinctive feature of our approach to modeling the labor market, and thus evaluating the model's ability to explain the data, is that we do not immediately impose a particular structural model of wage determination. Preferring to remain agnostic and let the data speak, we initially estimate the parameters of a reduced-form process for the real wage that is most consistent with the observed responses of quantities to our identified shock. Theoretically, our strategy is made possible by the fact that matching frictions imply that any wage that remains within the bargaining set is consistent with equilibrium. Empirically, our strategy is motivated in part by the lack of consensus over how flexible wages are in practice: Several important studies, including Haefke et al. (2013); Kudlyak (2014); and Basu and House (2016), have argued that real wages are flexible along the relevant margins, while recent work by Gertler et al. (2020) and Hazell and Taska (2020) has challenged these conclusions. As we describe below, we later use the parameters of the estimated reduced-form wage process to guide us towards a more structural and parsimonious model of wage determination that fits the data nearly as well despite having only a single free parameter.

Our estimation exercise delivers two main results. First, we find that the model—which has very few free parameters apart from the flexible wage process—does an excellent job at matching the impulse responses we find in the data. Second, we find that the implied wage process follows a distinctive pattern: Wages fall during the anticipation period ahead of the TFP shock, and then rise once the shock is realized. The estimated wage process is thus inconsistent with a model of extremely sticky real wages, but also hard to reconcile with a model of constant-share Nash bargaining, which cannot cause wages to fall significantly in response to higher expected future labor productivity.

A natural question then arises: What sort of wage-determination mechanism would be consistent with our estimated agnostic wage process? We show that our estimated wage process is consistent with a model in which wages are driven primarily by current cash flows, rather than the net present value of match surplus. We thus propose a simple model of wage determination according to which workers receive a pro rata share of firms' available cash flows after accounting for payments to capital and the costs of hiring. This model of wage determination closely resembles the model studied by den Haan and Kaltenbrunner (2009), and entails only a single free parameter. We re-estimate our model using the flow-based wage determination mechanism and show that the model fit, the model-implied impulse responses, and the implied wage are all virtually identical to the results from the fully agnostic wage specification we originally estimated.

Our proposed model of wage determination has two key elements. First, the wage splits current-period cash flows, rather than the present discounted value of match surplus, as in Nash bargaining. This feature is essential for matching the large observed responses of employment and output during the period of anticipation of a productivity change: In our model, good news about the future stimulates hiring today via the frictional matching process, which in turn increases employment, reduces labor's marginal product and cash flows per worker, and so reduces wages. When the shock is finally realized and labor becomes more productive, the wage rises in response to the increased revenue flows associated with higher productivity.

Because it is based on a present value calculation, a Nash bargained wage could never support a similar expectations-driven boom. For, any potential boom in employment and consumption today would lower future consumption growth, raising the present value of future cash flows and hence the Nash bargained wage itself. This negative feedback precludes a model with simple Nash bargaining from generating a boom in output and employment ahead of the realization of the shock.

Second, for our model of wage determination to match the data, the fraction of flow surplus accruing to households must be relatively high. This feature is closely related to the observation of Hagedorn and Manovskii (2008) that when firms receive a small fraction of flow surplus, small changes in productivity translate to large (in percentage terms) changes in flow profits and thus have an outsize effect on vacancy posting incentives. This effect is capable of generating large booms in response to *anticipated* changes in productivity because matching frictions pull forward the benefits of hiring, but only when those benefits are not offset by a forward-looking wage process such as Nash bargaining.

We conclude our main results by showing that the wage process we estimate is consistent with a variety of existing measures of the aggregate wage. To do this, we consider a panel of 19 commonly used wage measures collected from various sources. Our first (and preferred) measure of the wage is aggregate wage and salary payments to labor in the private sector (compiled by the BEA) divided by total private sector hours worked. The response of this wage to our identified shock is in fact very similar to what our model predicts: The wage falls on impact and then eventually rises following TFP.

In addition to the BEA aggregate wage series, we present a set of aggregate and sector-level wage series prepared by the BLS, and the new-hire wage series generated by Basu and House (2017). The responses of these variables to our identified shock differ substantially, but two patterns emerge. First, of the 19 series, the large majority fall on impact according to our point estimates, and only one is (just) significantly positive. Second, virtually all of the wage series exhibit upward-sloping patterns shortly after the identified shock. In these respects, our panel of wage data is quite consistent with the wage process we estimate; indeed, our estimated wage process lies within the range of estimated responses in the panel for at least 10 years after the shock.

Beyond the evidence on wages, we show that our model also implies empirically plausible responses of several key labor market variables not used as targets in our estimation procedure. In particular, our model delivers a substantial increase in labor force participation in anticipation of future productivity increases, as the tight labor market draws workers into the labor force. The model also matches empirical patterns for vacancy posting, hours, unemployment, and job-finding probabilities.

Since our model of wage determination is structural in the sense of depending on an economically meaningful quantity (cash flows), we also show that it can qualitatively match the effects of another important macroeconomic shock: *surprise* productivity. To do this, we extend our structural VAR identification strategy to isolate the shock that explains all remaining impact surprises to productivity, after controlling for the identified news shock. Our estimates show that this shock is quite large (indeed, it accounts for the bulk of business-cycle frequency fluctuations in productivity) but that it has much smaller implications for real quantities. In particular, employment only moves insignificantly while wages increase strongly in response to the shock. Our model of cash-flow based wage determination, which was estimated to match the large labor market responses to news shocks alone, can also match these out-of-sample patterns in the data. These results highlight how our model of wage determination is both robust to the shock under consideration and very different from simply assuming a sticky real wage.

Our results lead us to the conclusion that news about technology could well play an important role in driving the business cycle, including for the labor market, both in theory and in practice. Our empirical results are therefore related to a long literature seeking to identify news shocks in VARs, including important contributions from Beaudry and Portier (2006); Barsky and Sims (2011); Barsky et al. (2015), and more recently Kurmann and Sims (2020) and Bouakez et al. (2019). In particular, our conclusions contrast with those of Barsky et al. (2015) and Kurmann and Sims (2020)—a point we discuss in Section 2.4—but are similar to those in Portier (2015) despite our different approach to identification. Recently, Faccini and Melosi (2020) have estimated a structural labor search model with sticky wages and, like us, find that expectations shocks play a crucial role in driving the labor market. Our semi-structural empirical approach reinforces these findings, and allows us to easily incorporate additional evidence on how wages respond to news shocks.

From a theoretical perspective, our paper is most related to den Haan and Kaltenbrunner (2009), which motivates our choice of a structural wage-determination mechanism. That paper was among the first to demonstrate that news shocks can, in principle, drive an immediate expansion in employment. We build on that paper by providing new empirical evidence in support of news shocks and showing that a neoclassical model can quantitatively match the empirical responses of macroeconomic aggregates generated by such shocks, particularly measured investment. Theodoridis and Zanetti (2016) consider a search and matching model with Nash bargaining and several shocks, including news about TFP. While they find that news shocks are important for explaining consumption and investment dynamics, their model requires both job destruction shocks and shocks to the matching function to account for labor market dynamics. We provide quantitative evidence that news shocks alone can offer a compelling account of business cycles—including labor markets—with the right wage-setting mechanism. We thus stress the interconnectedness of the underlying source of fluctuations in the economy and the mechanism through which wages are determined.

Finally, the paper is related to Christiano et al. (2016), who also carry out an impulse response matching exercise with a labor search model. However, they do not consider the possibility of news shocks, which appear to be crucial in our data. Hall (2017) has argued that the data support a strong connection between stock market valuation and labor markets, a finding which our empirical and theoretical exercise supports.

The paper proceeds as follows. In Section 2, we describe our empirical strategy aimed at identifying TFP news shocks. Section 3 describes a theoretical labor search and matching model with an anticipated productivity shock. Section 4 estimates the parameters of the model, including a flexible reduced-form process for the wage, needed to match our empirical impulse responses, and discusses the implications of the estimation exercise for a plausible model of wage determination. Section 5 proposes a cash-flow based model of the wage, shows that this model provides a strong fit for the data both in and out of sample, and studies the model's implications for surprise TFP shocks. Section 6 concludes with directions for future research, including potential microfoundations for our cash-flow based model of wage determination.

2 Empirical Strategy

Our baseline empirical specification consists of a vector-autoregression of the form

$$\mathbf{Y}_t = B(L)\mathbf{Y}_{t-1} + A\epsilon_t, \tag{1}$$

where $\mathbf{Y}_t$ is a vector of observed variables, $B(L)$ contains the weights on past realizations of $\mathbf{Y}_t$, ϵ_t is a vector of structural economic shocks, and A is the structural matrix that our procedure seeks to identify from the set of reduced-form residuals, $\mu_t \equiv A\epsilon_t$.

We take as our baseline set of variables $\mathbf{Y}_t \equiv [TFP_t, GDP_t, C_t, I_t, N_t, SP_t]'$, which includes utilization-adjusted TFP from Fernald (2014), real per-capita GDP, real per-capita consumption, real per-capita investment, per-capita employment, and the real stock price. We estimate the VAR in levels via OLS and include four lags in the polynomial $B(L)$. Our sample ranges from 1960Q1 to 2018Q4. Additional details on data construction are provided in Appendix D.

We also consider a set of auxiliary variables, $\mathbf{W}_t$, that includes 19 measures of the hourly wage drawn from several sources, a set of additional labor market indicators, two measures of technological innovation, and inflation. These series are related to current and past observations of $\mathbf{Y}_t$ according to

$$\mathbf{W}_t = C(L)\mathbf{Y}_t + v_t \tag{2}$$

where the coefficient matrix $C(L)$ includes the same number of lags (four in our baseline) as the VAR in (1) and is estimated via OLS. We can thus construct impulse responses for any variables in $\mathbf{W}_t$ using the responses of the variables $\mathbf{Y}_t$ and the estimated values of

$C(L)$. This approach to computing auxiliary impulse responses is drawn from the factor-augmented VAR literature (Bernanke et al., 2005), and it assumes that the variables in $\mathbf{Y}_t$ contain all of the information relevant for forecasting aggregate TFP. Since our identification procedure, along with all of the related procedures we cite, already requires this assumption to accurately identify news, imposing it here is not restrictive.

2.1 Identification Approach

Our approach to identifying news shocks falls in the family of "max-share" approaches first introduced by Faust (1998) and Uhlig (2003), and adapted by Barsky and Sims (2011); Kurmann and Otrok (2013); Francis et al. (2014); Kurmann and Sims (2020); and Angeletos et al. (2020) among others. These approaches identify the shock which explains the largest portion of some covariance matrix implied by the model in (1). In our baseline procedure, we seek to identify the shock that explains as much as possible of the fluctuations in expected productivity at relatively long horizons in the future.

To state the identification assumption more formally, rewrite (1) in its MA(∞) form: $\mathbf{Y}_{t+k} = \sum_{k=0}^{\infty} \Gamma_k \hat{A} q \epsilon_{t-k}$, where $\hat{A}$ is the Choleski factorization of $cov(\mu_t) = \hat{A}\hat{A}'$ and q is an orthonormal matrix. The time-t forecast revision of expected productivity at horizon k is given by

$$E_t[TFP_{t+k}] - E_{t-1}[TFP_{t+k}] = e_1 \Gamma_k \hat{A} q \epsilon_t, \tag{3}$$

where e_1 is the basis vector selecting the first element of $\mathbf{Y}_t$.

Our objective is to identify the first shock as that which best explains the variance of forecast revisions at horizons between $\underline{k}$ and $\bar{k}$. That is, we want to find

$$q_1^{news} \equiv \max_{q_1} \sum_{k=\underline{k}}^{\bar{k}} e_1 \Gamma_k \hat{A} q_1 q_1' \hat{A}' \Gamma_k' e_1' \quad \text{s.t.} \quad q_1' q_1 = 1 \tag{4}$$

where q_1 is the first column of q. This problem can be solved by solving an eigenvalue problem, as described in the papers cited just above. Structural impulse responses can then be computed using the MA(∞) representation

$$\mathbf{Y}_{t+k} = \sum_{k=0}^{\infty} \Gamma_k \hat{A} q_1^{news} \epsilon_{t-k}. \tag{5}$$

We set $\underline{k} = 20$ and $\bar{k} = 80$, so that our identification will capture forecast revisions pertaining to productivity between 20 and 80 quarters in the future. By comparison, the approach advocated by Kurmann and Sims (2020) sets $\underline{k} = 0$ and $\bar{k} = 80$, while Barsky et al. (2015) set $\underline{k} = \bar{k} = 20$ and add to (4) the constraint that the impact effect of the news shock is exactly zero.

Our approach to identification is motivated by two primary considerations. On the one hand, we want to take seriously the concern raised by Kurmann and Sims (2020) and Bouakez et al. (2019) that the measure of TFP may be polluted by short-term measurement errors that, if systematically responding to business cycles, could make the imposition of a hard zero on impact incorrect. Hence, we want to avoid making the strong zero-impact restriction that Barsky and Sims (2011); Barsky et al. (2015); and Portier (2015) have made.

On the other hand, we also want to avoid designing an identification scheme that actively rewards non-zero impulses early on in the response. When $\underline{k} = 0$, however, the objective in (4) is influenced by such short-term effects, meaning the procedure will tend to mix short-term surprises and longer-term anticipated fluctuations in TFP. If the response to TFP differs across horizons then the approach will confound the different responses. Whether this issue is quantitatively important depends on the size and persistence of surprise productivity shocks in the data.[1] We briefly compare the results from our procedure with these alternatives in Section 2.4.

2.1.1 Identifying Surprise TFP

In Section 5.4, we also study our model's implications for identified *surprise* technology shocks. Intuitively, our procedure for identifying these shocks is to find the shock that explains the most of the instantaneous surprise in technology, after controlling for the effects of anticipated productivity shocks. Formally, we solve the problem

$$q_2^{surp} \equiv \max_{q_2} e_1 \hat{A} q_2 q_2' \hat{A}' e_1' \quad \text{s.t.} \quad q_2' q_2 = 1, q_2' q_1 = 0. \tag{6}$$

We will find that these shocks are fairly large and persistent, suggesting that the issue of confounding surprise and anticipated productivity when using the Kurmann and Sims (2020) approach may be substantial.

[1] Kurmann and Sims (2020) acknowledge this potential issue in Section V.D of their paper.

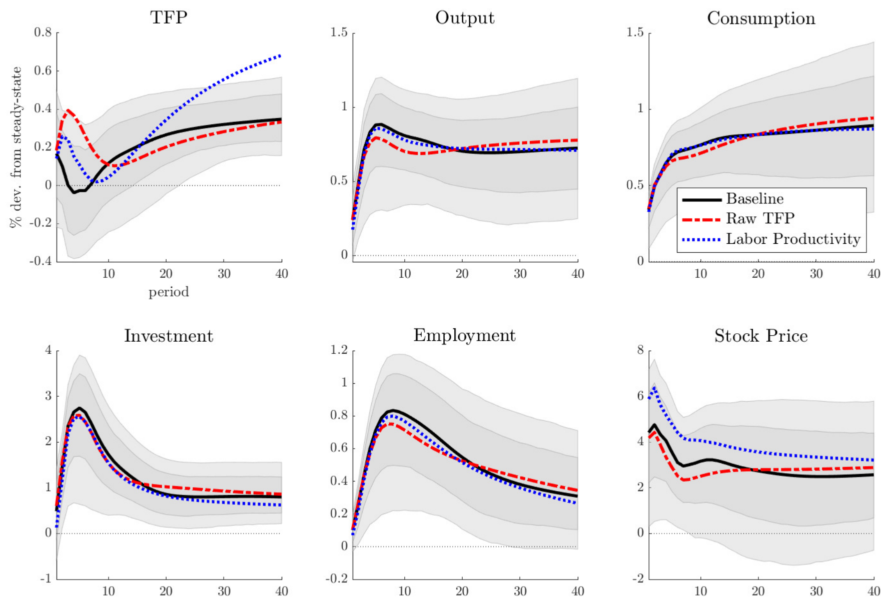

Figure 1: Impulse responses to the identified news shock. “Baseline” (solid black line) corresponds to the baseline specification with utilization-adjusted TFP. “Raw TFP” (dotted-dashed red line) replaces adjusted TFP with the Solow residual. “Labor Productivity” (dotted blue line) replaces adjusted TFP with labor productivity.

2.2 Results

Figure 1 presents the impulse responses to our identified shock, along with 68% and 90% confidence bands from a bias-corrected bootstrap. The solid black lines correspond to our baseline using utilization-adjusted TFP as described above—these are the results that we focus on throughout the paper. The blue dotted lines and the red dotted-dashed lines replace utilization-adjusted TFP with two alternatives—we return to these alternative results in Section 2.4 below. Focusing on the baseline results, on impact of the shock, TFP is slightly elevated, though insignificant, then falls modestly for several quarters, before it begins a gradual rise that becomes statistically significant after between three and five years. This pattern of productivity is consistent with the “technology diffusion” pattern emphasized by Portier (2015) in his comment on Barsky et al. (2015). The figure shows that our shock drives large and significant immediate fluctuations in output, consumption, investment and employment, as well as a significant increase in stock prices. Moreover, while the responses of most of these variables are larger in the short run, they are extremely persistent, with both output and consumption significantly positive ten years after the shock.

Table 1: Variance decompositions of VAR variables

Frequency (Quarters)	TFP	Y	C	I	N	NYSE
Business Cycle (6-32)	0.07	0.53	0.75	0.50	0.57	0.29
Medium run (32-100)	0.09	0.61	0.86	0.52	0.62	0.22
Long run (100-500)	0.58	0.88	0.88	0.74	0.66	0.42

Table 1 presents the variance decomposition for our shock across three portions of the spectrum, corresponding to business-cycle frequencies (6-32 quarters), medium-run frequencies (32-100 quarters), and long-run frequencies (greater than 100 quarters). The table shows that all of the quantity variables are substantially explained by the identified shock, with the contribution of the shock rising to well over 50% at longer horizons for all variables other than the stock market.

Crucially (and consistent with the finding of Angeletos et al., 2020), we find that TFP fluctuations are essentially orthogonal to the effects of this shock at business-cycle and even at medium-run frequencies. It is only at periodicities of over 100 quarters that the strong connection between our shock and productivity appears. These results are precisely consistent with the idea that expectations about very long-run productivity are playing a central role in driving fluctuations at shorter horizons, echoing the theories and structural estimation results of Blanchard et al. (2013) and Chahrour and Jurado (2018).

To understand the effect that the shock has on real wages, we produce impulse responses for a number of empirical wage measures to our identified shock. These wage responses are displayed in Figure 2. Our preferred measure of the aggregate wage (aggregate wage and salary payments to labor in the private sector divided by total private sector hours worked) displays two distinctive features. First, the wage falls modestly on impact. Second, the wage grows quickly as TFP begins to rise. The responses of the other wage series exhibit considerable heterogeneity but generally reflect similar patters: At their point estimates, the large majority fall on impact, just one is significantly positive, and nearly all of the series appear to grow over the horizon of the response.

Thus, the data appear to suggest that productivity news shocks could potentially play a central role in driving business-cycle fluctuations, as well as longer-term changes in macroeconomic aggregates. Moreover, in order to do so, the data suggest that wages should fall before eventually rising to keep pace with the eventual rise in productivity. We explore these patterns theoretically in the remainder of the paper. Before doing so, however, it is useful

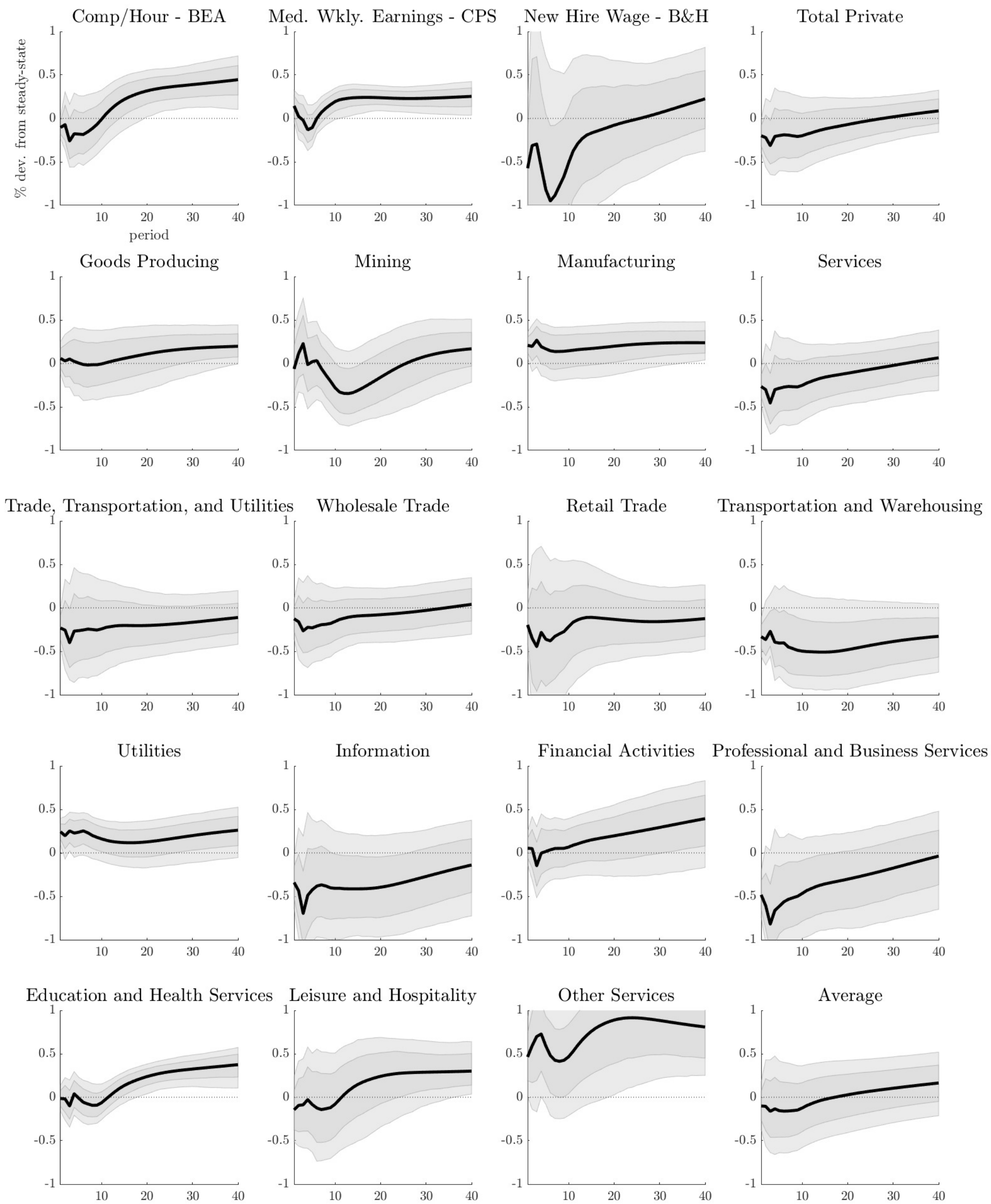

Figure 2: Wage responses to the identified news shock

to first provide some additional evidence that we have, in fact, identified a news shock, and also to relate our results to the results that would obtain under the other news identification approaches discussed above.

2.3 Evidence from Innovation Measures and Inflation

As further evidence, we next study the implications of our shock for three additional variables: two technological innovation measures (a novel index of information and communication technology standards from Baron and Schmidt (2017), and real per-capita R&D expenditures) as well as inflation.[2] We note that we are not the first to look to these variables for external evidence that we have identified a news shock: Kurmann and Sims (2020), who use a different approach to identifying news shocks, argue that the responses of these two variables to their shock support the news interpretation.

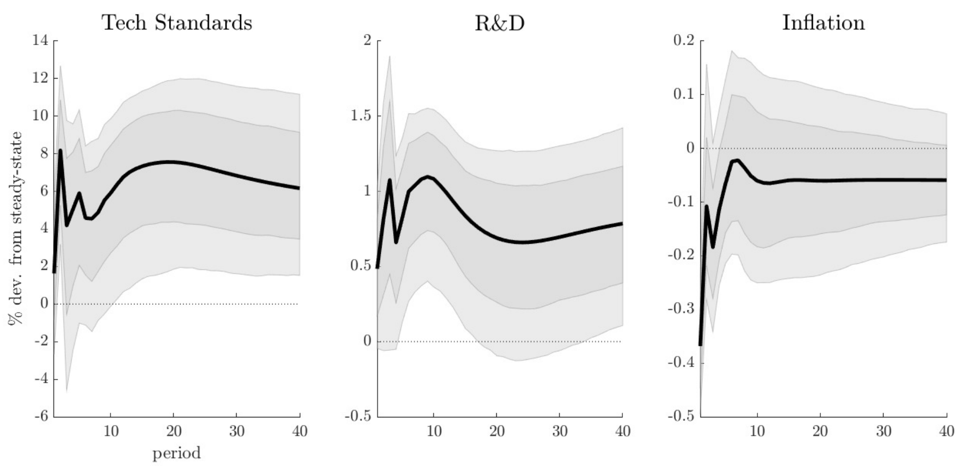

Figure 3: Measures of technological innovation and inflation

The first two panels of Figure 3 report impulse responses of the two technological innovation variables to the shock we have identified. The left-most panel indicates that the index of technological standards rises on impact, becomes significant at the 90% level in the following period, and after several additional periods becomes robustly significant for the remainder of the 40-quarter horizon. The fact that the technical standards series rises so quickly, even

[2]While the R&D and inflation series are familiar, the index of technological standardization from Baron and Schmidt (2017) warrants some discussion. Standards, the authors write, should be understood as "clearly identified documents which describe detailed features of a technology." Prominent examples include standards for electricity plugs, paper size formats, or 4G telecommunications. The authors measure the number of new standards in the information and communication technology industry at a quarterly frequency between 1960 and 2014. To relate their measure to news about future productivity, they argue that standardization "precedes the implementation of new technologies and signals future productivity gains."

though such standards take time to develop and adopt (see Footnote 2), suggests to us that it is unlikely that technology improvements are endogenously responding to some other force in the economy that might have independent effects on the business cycle.

The center panel depicts the response of R&D expenditures to our identified shock. This response, together with the response of the technological standards index, is helpful in determining whether we should be concerned that our measure of TFP is partially endogenous. Specifically, one common story of endogenous TFP involves shocks to the R&D sector. Such a shock would be expected to increase R&D on impact, and then be *followed by* an increase in technological standards. However, this is not the pattern we find. Rather, we find that R&D expenditures rise on impact and become significant at the 90% level after roughly a year—a response that does not clearly lead the increase in technological standards. Furthermore, even if this story were playing an important role in the data, it is not clear that the macroeconomic implications would be so different from our TFP news interpretation: Shocks to aggregate TFP or the productivity of R&D both give rise to forecastable changes in aggregate productivity, which of course is the object that matters to most participants in the economy.

Finally, the right-most panel of Figure 3 also shows the response of inflation to our identified shock. The point estimate of the impact effect is negative and significant at the 90% level, consistent with existing literature on the effects of news shocks.

2.4 Relationship to Other News Shock Procedures

Our approach to identifying anticipated productivity shocks is most closely related to Barsky et al. (2015) (BBL) and Kurmann and Sims (2020) (KS), and indeed in many circumstances the three approaches seem likely to yield similar results. However, our discussion in Section 2.1 suggests that in the presence of substantial surprise TFP shocks, or systematic measurement errors, our approach may prove more robust.

Figure 4, which plots the estimated TFP responses to news shocks under the different identification procedures (holding constant all other aspects of our VAR as described above), provides some evidence to suggest that these issues matter in practice. First, the *eventual, steady rise* in TFP always occurs earlier following the BBL shock than following our shock. This is true in all samples, but is especially visible in the 2007 sample, where TFP begins to rise in the period following the BBL shock, much sooner than it responds to our identified shock. Of course, because we do not impose a zero-impact restriction while the BBL approach

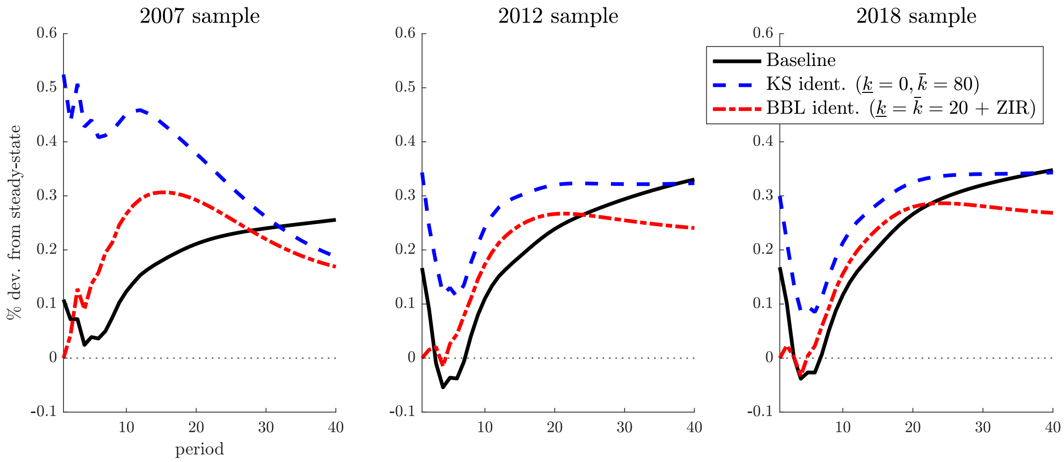

Figure 4: Productivity responses under different identification assumptions. "Baseline" targets horizons from 20 to 80 quarters ($\underline{k} = 20$, $\bar{k} = 80$). "KS identification" targets horizons from 0 to 80 quarters ($\underline{k} = 0$, $\bar{k} = 80$) following Kurmann and Sims (2020). "BBL identification" targets a 20-quarter horizon and imposes a zero-impact restriction ($\underline{k} = \bar{k} = 20$ + ZIR) following Barsky et al. (2015). All other aspects of the VAR are as in our main specification.

does, our shock induces an (insignificant) rise in TFP on impact, but the *steady* rise following our shock is more evocative of technological diffusion news. For other sample periods, the BBL identification yields responses that are more similar to what we find, but different from the 1960-2007 sample period.

Second, the impact and short-horizon effect on TFP induced by the KS shock always lies strictly above the effect induced by our shock, whereas the long-run effect on TFP (i.e., after 40 quarters) is always greater in response to our shock. Indeed, in two of the three sample periods, the level of TFP is greater on impact than it is after 40 quarters following the KS shock. This difference is explained by the fact that Kurmann and Sims (2020) assign positive weight to short-horizon movements in TFP along with longer horizon fluctuations.

Another way to assess the robustness of our approach to potential mismeasurement is to compare our results when we use measures of productivity that *we know* are systematically influenced by business-cycle developments, such as the unadjusted "raw" TFP series (Solow residual) and labor productivity. Both of these variables are quite likely to be influenced by variable capacity utilization, fluctuations in labor force composition, etc., but they should also be cointegrated with the exogenous component of productivity in the long run.

The red and blue dashed lines in Figure 1 show what happens when we replace our baseline adjusted-TFP measure in $\mathbf{Y}_t$ with these respective alternatives. The results for endogenous variables are all extremely similar to our baseline. This happens even though the short-run responses of raw TFP and labor productivity are quite different from our preferred utilization-adjusted TFP series. At longer horizons all three variables exhibit very similar profiles.[3] This is another demonstration of why it may be helpful to target only longer-horizon responses for the identification of news shocks.

2.5 Summing Up

With our identified news shock in hand, we now turn to understanding the effects of news theoretically. A key challenge in this regard is that it is difficult to get employment to rise in anticipation of future productivity. Neoclassical models cannot do so, because the marginal productivity of workers does not immediately change while the wealth effects of increased future income discourage current labor supply (Barro and King, 1984). Standard New Keynesian models also cannot match the patterns we have uncovered above because, to the extent they can generate news-driven expansions, they require a positive output gap and therefore counterfactually high inflation during the periods of anticipation of the future increase in productivity.

Search and matching models of the labor market offer one natural way to circumvent these two challenges. Specifically, forward-looking hiring decisions associated with search frictions imply that if the discounted stream of dividends from hiring a worker increases, then labor demand increases *today*, creating a force for employment to rise in response to good news about the future. Moreover, this effect does not depend on nominal rigidities, avoiding the counterfactual implication of high inflation during the period of anticipation. In the rest of the paper, we show how search frictions can explain our empirical findings and establish the key features of the wage-determination process that are needed to do so.

3 Model

The economy consists of a representative household and a representative firm who each trade in markets for consumption, labor and capital. Consumption and capital markets are competitive, while transactions in labor markets are subject to search and matching frictions in the spirit of Mortensen and Pissarides (1994).

[3] Note that labor productivity is "scaled up" because of the presence of the capital-labor ratio in that measure, which is cointegrated with productivity in the long run.

3.1 Households

The representative household consists of a continuum of *ex ante* identical members who are either employed, searching for work, or out of the labor force. The household derives utility at time t from consumption according to the period utility function $U(C_t, F_t)$, where C_t is household consumption and F_t is the measure of household members in the labor force.[4]

Each period, the household dedicates a portion S_t of its members to search for a match in the labor market. Searching members match with probability p_t. Newly-created matches become productive within the period, so that total labor force participation of the representative household is given by

$$F_t = N_t + (1 - p_t)\, S_t, \tag{7}$$

where N_t denotes the measure of currently matched workers and $(1 - p_t)\, S_t$ denotes the measure of searchers who failed to find a match in period t.[5] Each period, previously productive matches dissolve with exogenous probability λ, so that employment evolves according to

$$N_t = (1 - \lambda) N_{t-1} + p_t S_t. \tag{8}$$

In addition to choosing its consumption, the household also chooses a level of investment. The law of motion for the stock of capital is given by

$$K_{t+1} = (1 - \delta) K_t + I_t, \tag{9}$$

where δ is the depreciation rate of the capital stock.

The household budget constraint is thus given by

$$C_t + I_t + \tau_t = R_t K_t + W_t N_t + (1 - p_t) S_t \kappa_t + D_t, \tag{10}$$

where the consumption good is the numeraire. The household takes the rental rate of capital, the (real) wage rate of labor, and benefits paid to unemployed workers (R_t, W_t and κ_t respectively), as given. It also receives D_t, lump-sum dividends from firms, and pays τ_t, a lump-sum tax used to finance any exogenous stream of government expenditures and

[4]Consistent with the labor search literature incorporating a participation margin, we interpret non-participation in the labor force as leisure in the representative household's optimization problem.

[5]This timing convention is consistent with the evidence on labor market flows at quarterly frequency. See Davis et al. (2006).

unemployment benefits. The benefit paid to unemployed workers is assumed to be a fixed fraction of the current wage rate, $\kappa_t = \kappa W_t$.

The representative household's problem may thus be expressed as

$$\max_{C_t, I_t,, K_{t+1}, S_t, N_t} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, N_t + (1-p_t)S_t) \qquad \text{s.t. (8), (9) and (10)}$$

where we have substituted the expression for labor force participation in (7) into the utility function. The first-order conditions for consumption, investment, and capital next period together yield a standard Euler equation,

$$1 = E_t \Big\{ \Omega_{t,t+1} \Big[R_{t+1} + 1 - \delta \Big] \Big\}, \tag{11}$$

where $\Omega_{t,t+1} \equiv \beta \frac{U_{C,t+1}}{U_{C,t}}$ is the household's stochastic discount factor. The first-order conditions for the measure of searchers and the stock of workers together imply the labor force participation condition

$$-\frac{U_{F,t}}{U_{C,t}} = (1-p_t)\kappa_t + p_t \left[W_t + (1-\lambda) E_t \left\{ \Omega_{t,t+1} \left(\frac{1-p_{t+1}}{p_{t+1}} \right) \left(-\frac{U_{F,t+1}}{U_{C,t+1}} - \kappa_{t+1} \right) \right\} \right]. \tag{12}$$

Together, equation (8) through (12) characterize the household's optimal decisions.

3.2 Firms

The representative firm chooses labor, capital and vacancy postings to maximize the present value of real dividends, discounted according to the household's stochastic discount factor. The firm produces output with a production function of the form

$$Y_t = F(K_t, X_t N_t), \tag{13}$$

where X_t is a non-stationary labor-augmenting technology shock.

Our main shock is a news shock about future X_t. Define the growth rate of productivity as $\gamma_{x,t} \equiv X_t / X_{t-1}$, and the long-run growth rate as γ_x. We assume that productivity growth follows an AR(1) process with news,

$$\log(\gamma_{x,t}/\gamma_x) = \rho_x \log(\gamma_{x,t-1}/\gamma_x) + \epsilon_{x,t-h}. \tag{14}$$

In equation (14), the shock $\epsilon_{x,t-h}$ first influences productivity at time t but is observed by agents at time $t-h$. We refer to h as the *time horizon* of the news shock.

The law of motion of employed labor from the firm's perspective is given by

$$N_t = (1-\lambda)N_{t-1} + q_t V_t, \tag{15}$$

where V_t denotes vacancies posted in the labor market and q_t denotes the probability of a vacancy returning a match. The firm's profit maximization problem is thus

$$\max_{V_t,N_t,K_t} E_0 \sum_{t=0}^{\infty} \beta^t U_{C,t} \left[Y_t - W_t N_t - R_t K_t - \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right) X_t V_t \right] \qquad \text{s.t. (13) and (15)} \tag{16}$$

where a_n is the steady-state cost of a vacancy and $\nu(\frac{V_t}{V_{t-1}})$ is a vacancy-adjustment cost, whose functional form is specified below. The total cost of posting a vacancy, $a_n + \nu(\frac{V_t}{V_{t-1}})$, is scaled by long-run TFP in order to ensure stationarity of the model. The first-order condition for capital is given by

$$F_{K,t} = R_t. \tag{17}$$

The first-order conditions for vacancies and employment, respectively, yield

$$\phi_t^N = \frac{1}{q_t}\left[X_t \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right) + \nu'\left(\frac{V_t}{V_{t-1}}\right)\frac{V_t}{V_{t-1}}\right) - E_t\left\{ \Omega_{t,t+1} X_{t+1} \nu'\left(\frac{V_{t+1}}{V_t}\right)\left(\frac{V_{t+1}}{V_t}\right)^2 \right\}\right] \tag{18}$$

$$\phi_t^N = F_{N,t} - W_t + (1-\lambda)E_t\left\{\Omega_{t,t+1}\phi_{t+1}^N\right\} \tag{19}$$

where ϕ_t^N is the Lagrange multiplier on (15).

The value of the firm is the net present value of its output less its payments to workers, capital, and for the posting of vacancies. In equilibrium, this corresponds to

$$V_t^{firm} = Y_t - W_t N_t - R_t K_t - \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right) X_t V_t + E_t\left\{\Omega_{t,t+1} V_{t+1}^{firm}\right\}. \tag{20}$$

Since observed stock returns also reflect the effects of firm leverage, we map changes in firm value to observed changes in stock prices using a leverage factor,

$$\Delta SP_t \equiv (\Delta V_t^{firm})^{\phi_{lev}}. \tag{21}$$

3.3 Government

The government runs a balanced budget, financing an exogenous stream of aggregate purchases G_t, along with unemployment benefit transfers $(1-p_t)S_t\kappa_t$, through lump-sum taxes τ_t:

$$\tau_t = G_t + (1-p_t)S_t\kappa_t. \tag{22}$$

To maintain balanced growth, we follow Schmitt-Grohé and Uribe (2012) in assuming that government spending adjusts to restore its long-run share of output, i.e.

$$G_t = G_{t-1}\gamma_{x,t-1}. \tag{23}$$

3.4 Wages

In search and matching models such as the one described above, the presence of matching frictions gives rise to positive match surplus that is split by the wage. Any wage yielding weakly positive surplus for the firm and the worker is consistent with equilibrium. The basic theory thus provides little guidance on how to model wage setting. Furthermore, there is considerable disagreement about the best empirical measure of wages, making it difficult to elicit direct empirical guidance regarding the best model of wage setting.

We therefore specify for our baseline an "agnostic" real wage, which places essentially no *a priori* structure on how wages can respond to shocks. In particular, we model real wage growth as an MA(H) process augmented with an error-correction term that ensures wages remain cointegrated with productivity in the long run. Specifically, we assume

$$\Delta w_t = \gamma(L)\epsilon_t - \phi_x(w_{t-1} - x_{t-1}), \tag{24}$$

where $w_t \equiv \log(W_t)$, $x_t \equiv \log(X_t)$, and $\Delta w_t \equiv \log(w_t) - \log(w_{t-1})$.

Accordingly, our wage process admits $H+2$ free parameters ($H+1$ associated with the polynomial $\gamma(L)$ plus ϕ_x). In Section 5, we propose a cash flow-based structural description of wages that contains only a single free parameter, and explore how well it can reproduce our agnostic estimates of the wage process described above.

4 Estimation and Results

4.1 Functional Forms

We assume matches between searchers and vacant firms, M_t, are generated by a standard Cobb-Douglas matching technology,

$$M_t = \chi V_t^{\epsilon} S_t^{1-\epsilon}. \tag{25}$$

This functional form has been popular in both the empirical and theoretical literature on account of its tractability and empirical success in describing the matching process (Petrongolo and Pissarides, 2001).

One common challenge for models of news is that, under standard preference specifications, wealth effects cause labor supply and/or labor force participation to fall in response to good news. To avoid this implication, we use preferences of the form suggested by Greenwood et al. (1988), modified as in García-Cicco et al. (2010) and Akinci and Chahrour (2018) to allow for balanced growth,

$$U(C_t, F_t) = \frac{\left(C_t - \psi X_t F_t^{\theta}\right)^{1-\sigma}}{1-\sigma}. \tag{26}$$

We assume that output is produced using a standard Cobb-Douglas production function,

$$F(K_t, X_t N_t) = K_t^{\alpha}(X_t N_t)^{1-\alpha}. \tag{27}$$

Finally, we assume that firms face a quadratic cost of adjusting vacancies, given by

$$\nu\left(\frac{V_t}{V_{t-1}}\right) = \frac{\xi}{2}\left(\frac{V_t}{V_{t-1}} - 1\right)^2. \tag{28}$$

As we discuss below, we directly calibrate α, χ, ψ, and a_n and estimate ϵ, θ, σ, and ξ.

4.2 Calibration

We calibrate a large set of parameters, since most of the structural (non-wage) parameters in our simple model are naturally pinned down by long-run averages in the data. Our calibration choices are summarized in Table 2. The relationship between our model's steady

Table 2: Calibrated Parameters

Parameter	Concept	Value
β	Discount factor	0.990
α	Capital share	0.320
δ	Depreciation rate	0.030
λ	Separation rate	0.120
ψ	Preference parameter	1.088
κ	Replacement rate	0.200
a_n	Vacancy posting cost (steady state)	0.290
ϕ_{lev}	Leverage factor	1.500
ϕ_x	Wage error-correction	0.050
γ_x	TFP growth (average)	1.004
ρ_x	TFP growth (persistence)	0.890
σ_x	TFP growth (innov std. dev.)	0.060

state and the calibration described below are derived in Appendix B.

We select the discount factor β to be consistent with an annual real interest rate of 4%. We fix capital's share of output and the capital depreciation rate to standard values of $\alpha = 0.32$ and $\delta = 0.03$, respectively. The equity leverage factor $\phi_{lev} = 1.5$ is set to be consistent with a long-run debt-to-book value of public firms of one-third. The quarterly job separation rate is set to $\lambda = 0.12$, consistent with a summary of the evidence in Yashiv (2008) and evidence since 2000 available from the JOLTS (Job Openings and Labor Turnover Survey) data from the BLS.

We use a replacement rate of unemployment benefits of $\kappa = 0.2$. This is at the low end of values typically used in the academic literature, but is close to the average replacement rate of 29% identified in the comprehensive Job Study from OECD (1994). A low value of κ is not necessary for our model to closely match the quantity data used in our VAR. However, it is important for matching out-of-sample data on labor force participation, which rises on impact of our shock, despite falling wages.[6]

To see why κ is important for the labor supply response in our model, consider the labor force participation condition in (12) with $\lambda = 1$:

$$-\frac{U_{F,t}}{U_{C,t}} = W_t \left[p_t + (1 - p_t)\kappa \right]. \tag{29}$$

[6]We discuss our model's implications for labor force participation and other out-of-sample moments below.

When $\kappa = 1$, this condition reduces to $-U_{F,t}/U_{C,t} = W_t$, so participation only responds to the fall in the wage, and is unresponsive to changes in market tightness and hence p_t. By contrast, when $\kappa = 0$, we have $-U_{F,t}/U_{C,t} = W_t p_t$, so a sufficiently tight labor market can draw workers into the labor force even if the wage falls.

We fix the size and persistence of the productivity news shock, as well as the horizon of its arrival, to be consistent with our point estimates of the TFP response to our identified shock. As depicted in Figure 1, there is a gradual build up of productivity after agents learn of the change. The implied values are $\sigma_x = 0.06$, $\rho_x = 0.89$, and $h = 9$.

As a final parameter, we need to fix a_n, the steady-state cost of vacancy postings. We follow Fujita and Ramey (2012), who draw on survey evidence on employer recruitment behavior cited in Barron et al. (1997) and Barron and Bishop (1985) to arrive at an estimate that vacancy posting costs constitute 17% of the marginal product of labor. This corresponds to a value of 0.29 for a_n, which in turn pins down the long-run level of the wage and thus labor's share of match surplus. In particular, the calibration implies that roughly 83% of match surplus flows to households in our model. This is similar to (although somewhat smaller than) the value used in Hagedorn and Manovskii (2008). See Appendix C for a derivation of the steady-state surplus share in our model based on the calibration strategy described above and elaborated on in Appendix B.

4.3 Estimation Procedure

We estimate our model parameters by matching model-implied responses following a news shock to their counterparts in our empirical VAR. The targets are the responses of all six of the variables in our baseline VAR (that is, $\mathbf{Y}_t$) for horizons of up to 40 periods.[7] Because we aim to match 40 periods, we fix the horizon of the MA terms in the wage process at $H = 40$.

Let $\hat{\psi}$ denote the column vector stacking our point estimates of each of these impulse responses. Then our target objective function corresponds to

$$\mathcal{L}(\Theta) = (\hat{\psi} - \psi(\Theta))' W (\hat{\psi} - \psi(\Theta)) \tag{30}$$

where $\Theta \equiv \{\theta, \sigma, \xi, \epsilon, \gamma_0, \gamma_1, ...\gamma_H\}$ is the vector of parameters we estimate and W is a diagonal matrix consisting of the inverse of the bootstrapped variances of each entry in $\hat{\psi}$.[8]

[7] Because we calibrate the parameters of the exogenous process for TFP in Table 2, including the impulse response of TFP in the target moments $\hat{\psi}$ is irrelevant for our results.

[8] Estimating the agnostic wage process occasionally delivers "jagged" responses near the end of the impulse

Table 3: Parameter Estimates (Agnostic Wage)

Parameter	Concept	Estimate	Std. Err.
θ	Labor supply elasticity	3.976	1.333
σ	Inv. intertemporal elasticity	2.058	0.471
ξ	Vac. posting cost (curvature)	0.500	0.171
ϵ	Matching function elasticity	0.751	0.025

One advantage of matching impulse responses is that it does not require a complete specification of all the other shocks that may buffet the economy. This approach is especially natural given our objective to discover if news *can possibly* account for the patterns in the data. Still, one might be concerned that the presence of other shocks in the true data could "confuse" our identification approach. To allay these concerns, we perform a VAR "suitability" exercise in Appendix E.3. There, we augment our model with additional structural shocks commonly used in the literature and show that our approach applied to simulated data still does a very good job at identifying the news impulse responses from our model.

4.4 Results

Table 3 reports our baseline estimates for the first four elements of $\hat{\Theta} \equiv \arg\min \mathcal{L}(\Theta)$ along with standard errors generated from the asymptotic delta method following Guerron-Quintana et al. (2017). For brevity, we refrain from reporting numerical values for each of the 41 parameters of $\hat{\gamma}(L)$, and refer the reader instead to the figures below for their implications for the wage. Our structural parameter estimates are largely in line with existing literature.[9]

Figure 5 plots the impulse responses from our empirical identification procedure against those implied by our estimated model in response to a news shock. The model fit is very good. Specifically, the model provides a remarkably strong account of the impact effect, as well as the subsequent trajectories, of output, consumption and the stock price in the data. The model-implied response of employment is also very close to the data, albeit slightly too

response horizon. For this reason, we augment the loss function (30) with a small penalty for acceleration (changes in the growth rate) of the wage. This penalty accounts for less than 1% of the loss function at the optimum and does not affect our results in any qualitative way.

[9]Estimates of the elasticity of the matching function with respect to vacancies, ϵ, tend to vary depending on the methodology and data. Our estimate is relatively high, but within the range reported in Petrongolo and Pissarides (2001) and similar to the value estimated by Yashiv (2000) (0.87).

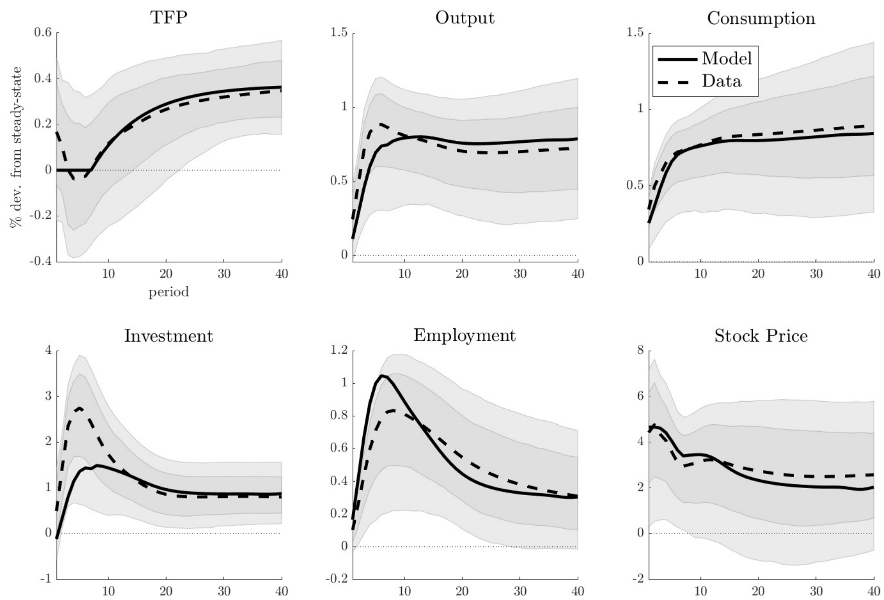

Figure 5: Quantity responses: Model (agnostic wage) and data

large over the first two years. The response of investment is somewhat muted on impact and in the first two years relative to the data, but quickly catches up.

Figure 6 plots the impulse response of our estimated agnostic wage process following a news shock. We overlay empirical impulse responses from our panel of 19 commonly used aggregate and industry-level wage series. The latter serve to highlight both the considerable heterogeneity in responses across various measures of the real wage, but also the presence of several systematic components of how wages respond to our shock. In particular, the large majority of the series fall on impact and eventually rise above their initial levels in response to the shock. As it happens, these features are precisely what we find in our agnostic wage process. Furthermore, it bears emphasizing that the model wage was in no way constrained to match these empirical patterns: Our estimation procedure relied on the six series in $\mathbf{Y}_t$ alone.

There are three principal take-aways from our estimation exercise: (i) A parsimoniously specified labor search and matching model with an entirely agnostic wage process can replicate the economy's dynamic response to a news shock; (ii) in order to do so, wages must fall on impact, remain low throughout the anticipation period, and rise quickly when the shock is realized; and (iii) such a wage response lies squarely within the range of empirical responses of wages to our identified shock, and is thus empirically plausible.

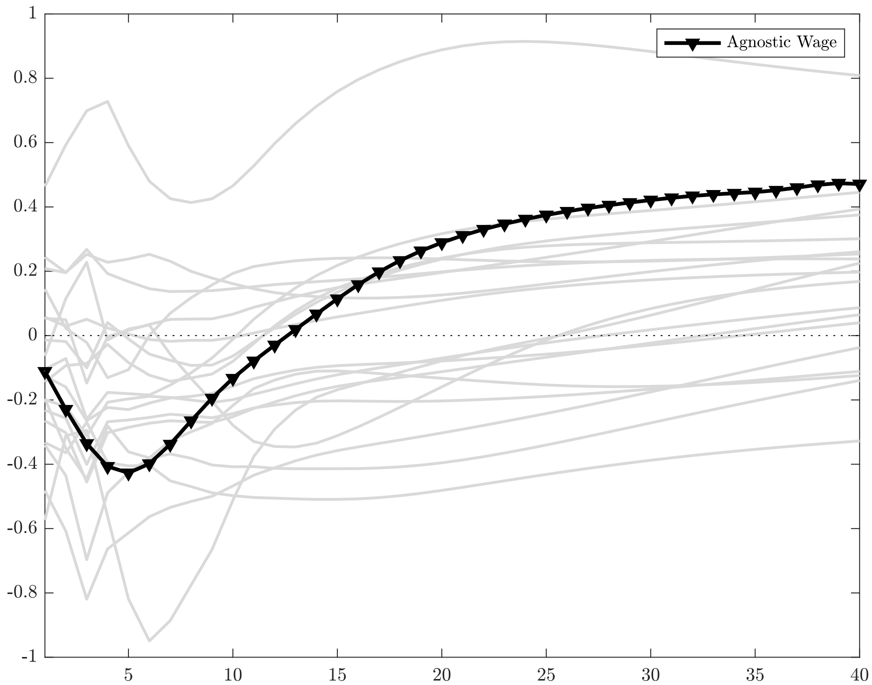

Figure 6: Wage response: Model (agnostic wage) and data (19 empirical measures)

Of course, any reduced-form specification of wages, however well it may fit the data, is most useful if it can inform the choice of a more structural theory of wage determination. We therefore take up the task of proposing such a theory of wage determination that reflects what we have learned from the preceding reduced-form exercise.

5 A Cash Flow-Based Model of Wage Determination

Is there a structural model of wage determination that is consistent with our estimated agnostic wage process—and thus consistent with the economy's dynamic response to a news shock?

Models in which wages depend explicitly on the *present discounted value* of match surplus, such as Nash bargaining, will struggle to generate sizable anticipation effects like those we observe in the data. This is because, in the presence of matching frictions, a forward-looking wage will rise, reducing the benefits of hiring today in anticipation of higher future productivity. Indeed, as discussed above, most standard measures of real wages fall on impact in response to our identified shock, suggesting that such models will be poor candidates for explaining either real quantities or real wages. Before proceeding, it is worth emphasizing that not all of the empirical wage series in Figure 2 fall in response to our shock, although most do. This suggests that, at least in those sectors for which wages remain relatively flat, a Nash-style forward-looking wage rule may prevail, at least based on the wage data.

In light of the preceding intuition, a natural alternative to Nash bargaining is a sharing rule based on some component of the *flow* value of a match, rather than the present discounted value of match surplus. We thus propose a simple model of wage determination according to which workers receive a share of firms' available cash flows after accounting for payments to capital and the costs of hiring. This model, and the intuition underlying it, is closely related to the model studied by den Haan and Kaltenbrunner (2009).[10] In particular, we consider a model in which wages are given by

$$W_t = \omega_0 P_t \tag{31}$$

where

$$P_t \equiv \frac{Y_t - R_t K_t - \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right) X_t V_t}{N_t}. \tag{32}$$

This process embodies the qualitative features towards which our estimated agnostic wage process directed us. Namely, it allows for wages to fall in response to expectations of a future increase in productivity, and then rise when that increased productivity is finally realized. Why does the wage fall in response to expectations of future productivity? In the world we consider, a strong labor market is one in which (i) employment is high, so the average product of labor is relatively low, and (ii) expenditures on vacancies are relatively high, so cash flows after accounting for posting and capital costs are relatively low. Thus the wage can fall and the economy can boom when good news about future productivity arrives.[11]

As a basis for comparison, we also consider the implications of a Nash bargaining protocol. Appendix C includes a derivation of the Nash bargained wage along with results for the implied dynamics of quantities following a news shock in that version of the model.

5.1 Estimation

We next re-estimate the structural model described in the preceding section, replacing the flexible agnostic wage process with a version of (31) intended to allow the data to choose

[10] In the Conclusion, we discuss some possibilities for how such a model might be explicitly microfounded.

[11] Our main results continue to hold if we instead define P_t as per-worker cash flows net of capital costs only, $P_t \equiv (Y_t - R_t K_t)/N_t$.

Table 4: Parameter Estimates (Flow wage)

Parameter	**Concept**	**Estimate**	**Std. Err.**
θ	Labor supply elasticity	3.155	0.316
σ	Inv. intertemporal elasticity	3.390	0.415
ξ	Vac. posting cost (curvature)	0.092	0.027
ϵ	Matching function elasticity	0.811	0.004
ω^F	Flow term	0.726	0.003

between our model and a simple inertial wage rule:

$$W_t = \omega_0 P_t^{\omega^F} W_{t-1}^{1-\omega^F} \tag{33}$$

where ω_0 is calibrated to match data on vacancy posting costs and thus implies the same steady-state wage as in the agnostic model (see Appendix B). Meanwhile, ω^F is directly estimated. The model is otherwise identical to the model described in Section 3, and the estimation procedure is likewise unchanged. Since we are no longer estimating the 41 parameters associated with the reduced-form MA(40) wage process, and are instead estimating a single parameter governing the importance of the flow wage component (ω^F), we are estimating 40 fewer parameters.

Table 4 reports results from our estimated model with the flow-based model of wage determination. Parameter estimates are broadly in line with the estimates from the model with the agnostic wage in Table 3. We estimate a slightly lower value for the labor supply elasticity (θ), a somewhat higher value for the inverse intertemporal elasticity of substitution (σ), and a significantly smaller role for the vacancy adjustment cost parameter (ξ). The elasticity of the match function (ϵ) is similar to our estimate in the agnostic model. We estimate a weight on the flow-component of our wage (ω^F) of 0.73 with tight standard errors, suggesting that, while some persistence is important, a strong link between cash flows and wages is important for the model to be able to explain the quantity data.

Figure 7 plots the impulse responses from our empirical identification procedure against those implied by our simple model of wage determination. Despite the fact that we now have 40 fewer degrees of freedom, the model fit remains very strong. Observationally, there is little difference between Figures 5 and 7, while the minimized value of the criterion is only modestly larger despite the parsimony of the model—both in terms of the underlying search

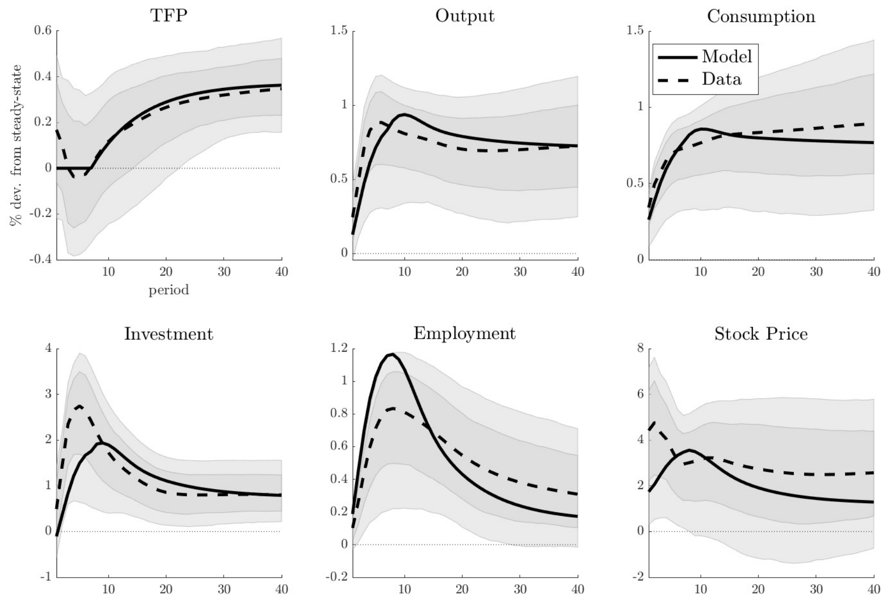

Figure 7: Quantity responses: Model (flow wage) and data

and matching structure and the single-parameter structural model of a flow-based wage.

To assess the correspondence between our estimated agnostic wage and our tightly-parameterized structural wage-determination model, Figure 8 plots the response of both estimated wage processes as well as our panel of empirical wage responses. We include our estimated Nash bargained wage as a point of comparison.

Our estimated flow-based model of the wage is nearly identical to the 41-parameter reduced-form wage process we estimated in the previous section. Furthermore, both series lie well within the range of the empirical wage responses to our identified shock, falling on impact and eventually rising when the shock is realized. The Nash wage, by contrast, adjusts by a negligible amount on impact, only rising once the productivity improvement is realized. The inability of the Nash wage to fall on impact makes it incapable of generating the large anticipation effects on output and employment that we observe in the data.

5.2 Flow Wage: Critical Features

The empirical success of our cash flow-based wage mechanism rests on two key elements. The first critical feature is that the wage depends on contemporaneous cash flows, not the present discounted value of match surplus. For a given real interest rate and wage, expectations about higher future productivity increase the incentive for firms to post vacancies ahead of

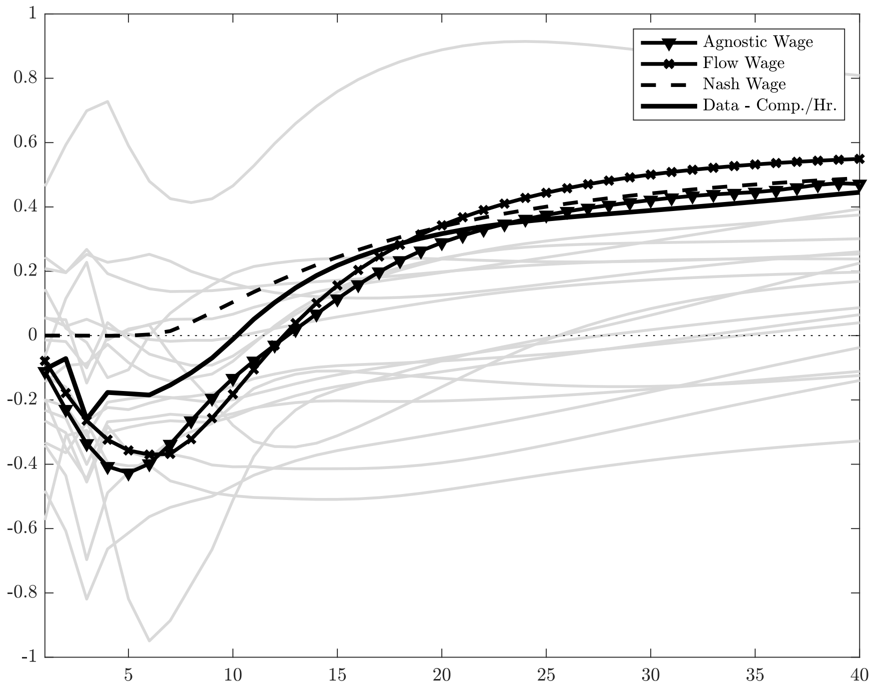

Figure 8: Estimated wage responses in data and model

the realization of the shock. The question for the different wage mechanisms then becomes: How do real interest rates adjust in equilibrium?

If wages split cash flows net of non-wage costs, news about future productivity does not directly feed back into the wage, so that current hiring, output, and consumption can rise in anticipation of the shock. Higher current output, in turn, drives down the current marginal product of labor and wages while higher current consumption mitigates the increase in the real interest rate, thus sustaining the increase in vacancy posting incentives.

As discussed above, our estimate of ω^F, the weight on the cash-flow component of the wage, implies that the flow wage process we describe is quantitatively important in accounting for responses to a news shock. It is instructive to reflect on why this number might not be even higher. Intermediate values of ω^F, such as the one we estimate, make wages somewhat sluggish: According to our estimates, wages do not rise until roughly 13 quarters after the shock, whereas TFP increases in the 9th quarter. This delay creates a persistent gap between future labor productivity and future wages that increases the value of a match today, thus stimulating vacancy posting and employment. The dependence on cash flows further decreases current wages, amplifying the effect on vacancies and current employment. With $\omega^F = 1$, this future productivity-wage gap does not occur, leaving no initial increase in vacancy posting for the flow wage processes to amplify.

By contrast, if wages are forward looking and depend on the present-discounted value of match surplus, then the conjectured increase in the value of vacancies will increase wages, decreasing current hiring and consumption, forcing up the real interest rate which further decreases the incentive to post vacancies. Through this negative feedback loop, the Nash bargained wage prevents a boom in anticipation of the future productivity, providing a result somewhat akin to the classic finding of Barro and King (1984), now adapted to the search economy.

This qualitative description of the mechanism that allows employment to rise in response to an anticipated shock is general, but the quantitative power of the mechanism relies on a second key feature: Flow profits must be small and thus relatively elastic in response to our identified shock. This observation is related to the insight of Ljungqvist and Sargent (2017), who observe that in a large class of matching models featuring surprise productivity shocks, a necessary condition for small and elastic profits is that the "fundamental surplus" must be small. Casting our model in terms of their steady-state decomposition of the elasticity of tightness with respect to productivity is not straightforward, however: In models featuring *anticipated* productivity shocks, such as ours, short-run dynamics are not necessarily well approximated by steady-state comparisons, as is the case with models featuring surprise productivity shocks.[12] Nevertheless, the insight that in the large class of models considered by Ljungqvist and Sargent (2017) flow profits must be small and elastic in order to achieve a large response in vacancy creation and unemployment also applies to our model.[13]

5.3 Non-targeted Moments

We next consider our model's implications for several widely studied features of labor markets that were not targeted in the course of estimation, including labor force participation, firm vacancy posting, and the Beveridge curve. We also discuss why a version of our model with nominal rigidities would likely yield falling inflation following a news shock, as we find in the data in Figure 3.

[12] See Shimer (2005) for discussion of this point.

[13] Of course, to be consistent with equilibrium, both firms and households must receive positive surplus in each period—otherwise endogenous separations would occur. In the long simulations in Appendix E.3, we find that the share of surplus accruing to workers fluctuates between 72% and 93%, well within the required bounds.

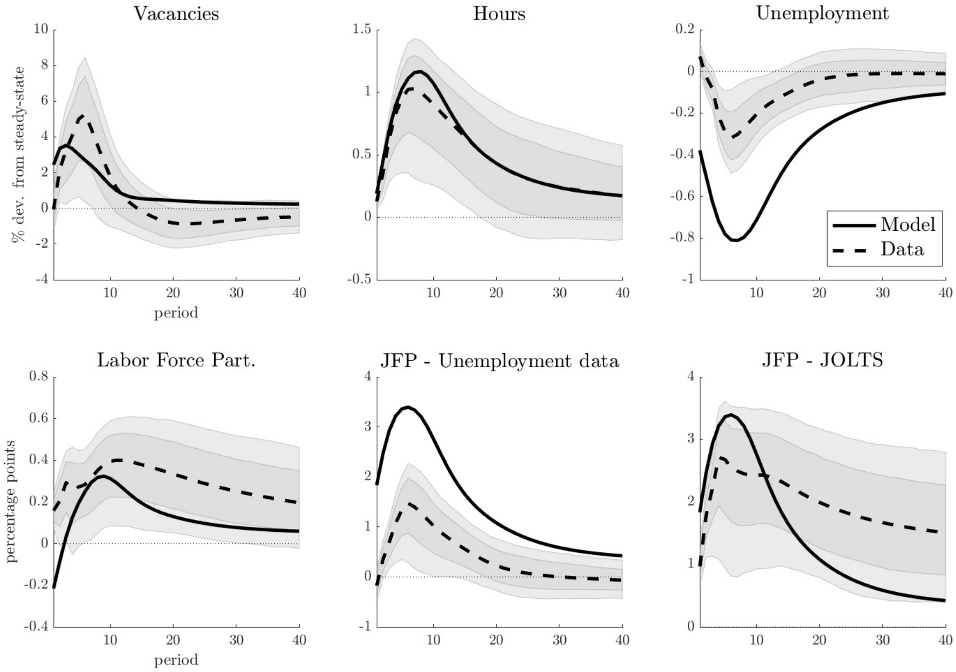

Figure 9: Labor market variables

5.3.1 Labor Market Variables

To evaluate our model's out-of-sample fit, Figure 9 plots impulse responses of five key labor market variables—vacancies, labor force participation, hours, unemployment, and two measures of the job-finding rate—in our estimated model and in the data. The responses of vacancies, labor force participation, and hours in our model are all broadly consistent with the empirical responses. The job-finding probability in the model moves too much relative to the empirical job-finding probability based on unemployment data, while an alternative measure of the job-finding probability based on JOLTS flow data is more in line with the model's response. The unemployment rate likewise moves too much in the model, although this is simply a mechanical combination of the model's employment response in Figure 7 (which is somewhat larger than in the data) and the model's labor force participation response in Figure 9 (which is somewhat smaller than in the data).[14]

[14]See Appendix D for details of data construction.

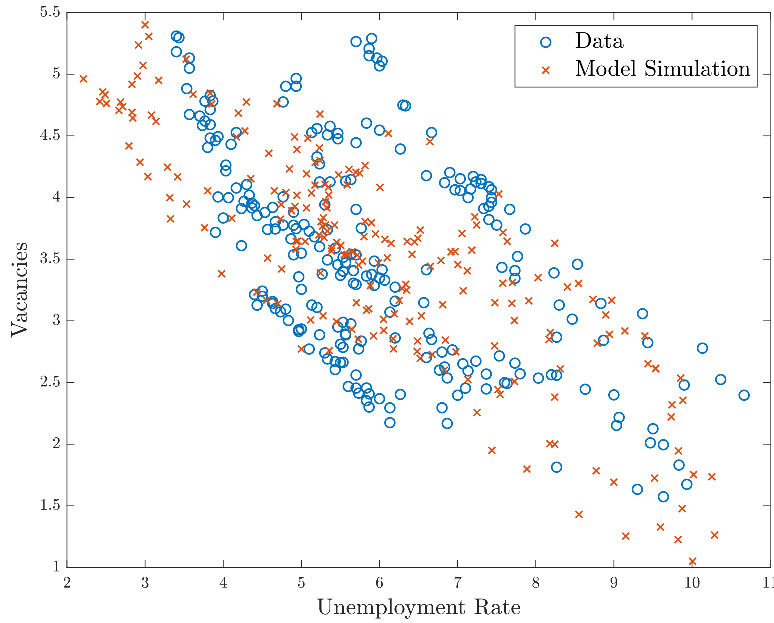

Figure 10: Beveridge curve

5.3.2 Beveridge Curve

Is our model consistent with the observed negative relationship between unemployment and vacancies in the data? Because of the presence of a labor force participation margin in the model and the fact that we focus on anticipated rather than surprise TFP shocks, the answer to this question is not immediately clear, either qualitatively or quantitatively. Accordingly, we compute the Beveridge curve using the most recent vacancy data (1960Q1-2018Q4) constructed as in Barnichon (2010), following the procedure of Elsby et al. (2015).

We estimate the slope of the Beveridge curve via OLS using the US data described above and find a value of −0.30. Performing the same analysis on data simulated from our model, we find a value of −0.38. Figure 10 plots the curve for historical data and a single simulation of the same length. We take the ability of the model to match this out-of-sample target as further evidence that our estimated model provides a strong account of labor market fluctuations.

5.3.3 Nominal Wages

While the model we study is entirely real, news shocks are often estimated to induce a fall in inflation (our analysis is consistent with this fact—see Figure 3). This leads to two questions: First, if we were to consider a model with nominal rigidities, would a news shock lead to a fall in inflation? Second, given the observed fall in inflation and real wages following our identified shock, do our results imply that news shocks lead to a decline in the level of nominal wages (that would be difficult to square with the data, in which average nominal wages rarely decline)?

Regarding our model's implications for inflation, there is good reason to think that if we were to add nominal rigidities to our model (say, in the form of sticky prices), the news shock would generate a fall in inflation. The reason for this relates intimately to the cash-flow sharing rule for the wage that we find can account for quantity responses to a news shock. Specifically, in a broad class of sticky-price models, inflation can be expressed as a function of the present discounted value of future real marginal costs (see, e.g., Barsky et al. 2015). Following our shock, real wages fall on impact and continue to fall, whereas TFP remains constant for a number of periods. This suggests that future real marginal costs will fall following the realization of the news shock, which in turn implies a fall in inflation on impact, precisely as we observe in the data.[15] Essential to this argument is the fall in real wages implied by our wage rule—a response that does not obtain under, e.g., Nash bargaining.

Regarding the implications of our empirical results for nominal wages, a back-of-the-envelope calculation suggests that the level of nominal wages does not actually fall in response to our shock. To see why this is, suppose that steady-state nominal wage growth is 2% annually (or 0.5% on a quarterly basis), consistent with 2% annual steady-state inflation.[16] Then, to determine whether the level of nominal wages ever falls following our identified shock, we can use the observed response of wages in Figure 8 and the observed response of inflation in Figure 3, to compute the implied quarterly nominal wage inflation rate, expressed as percent deviations from the steady state. The resulting nominal wage inflation never falls below -0.35%. Because this is smaller in absolute value than the 0.5% steady-state nominal wage growth, our estimates imply that nominal wages do not actually fall in response to our identified shock.

[15] In the context of a model with a frictional labor market, real marginal costs include both unit labor costs (as in the benchmark New Keynesian model) and an additional term representing unit hiring costs relative to expected hiring costs in the future (Krause et al., 2008). However, this second component is likely to be small and relatively unimportant compared with unit labor costs, so the basic intuition from the frictionless model—that inflation dynamics are driven by unit labor costs—should still hold.

[16] This is actually a lower bound because productivity growth also contributes to nominal wage growth.

5.4 Unanticipated Productivity Shocks

Given the empirical success of the cash flow-based model of wage determination in accounting for responses to anticipated productivity shocks, it is natural to ask whether the model's implications for the effects of *unanticipated* productivity shocks are likewise consistent with the data. To address this question, we compare our model's implications for surprise shocks to those we identify in the data using the extension of our identification procedure described in Section 2.1. This is a particularly challenging test for our model, since the structural parameters have been estimated only to match the empirical responses to *anticipated* productivity shocks.

Figure 11 reports the empirical and model-implied impulse responses for TFP, wages, employment and output.[17] The empirical TFP response is fairly well approximated by an AR(1) process, which we therefore assume in the model, choosing the standard deviation of the innovations and the autocorrelation parameter to approximate the empirical response of TFP to our identified shock.

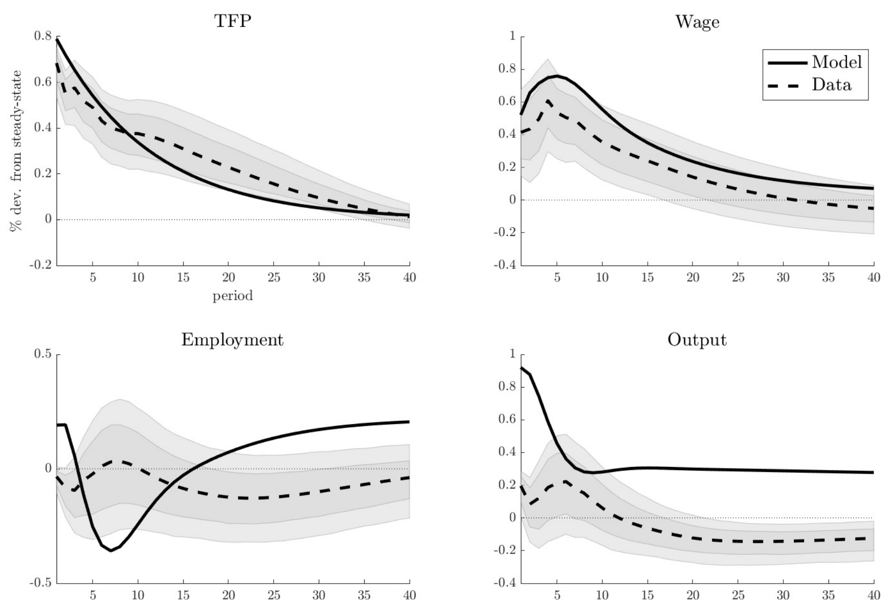

Figure 11: Unanticipated productivity shock

Empirically, the results in Figure 11 indicate that the surprise TFP shock that we identify in the data has effects similar to those found in the New Keynesian literature: Positive TFP

[17]For the empirical wage we report the response of a simple average of the wage series from Figure 2.

surprises induce small or even negative effects on employment and correspondingly muted effects on output (Gali, 1999; Basu et al., 2006). Even though our model has not been estimated to match these responses, the theoretical impulse responses in Figure 11 accord well with this story. Most notably, the top right panel highlights that our flow-based model of wage determination provides a remarkably similar response to the TFP shock compared with the response of wages that we identify in the data. Specifically, in both the model and the data, wages rise significantly on impact, continue to rise for several quarters, and then slowly die down—patterns that will be difficult for common models of slowly adjusting real wages to accommodate. In turn, the strong response in real wages allows the model to generate a tepid response in employment (note the scaling of the vertical axis in the bottom left panel), which is consistent with the muted empirical response which rarely deviates significantly from zero. While the model implies too large of an impact effect on output, the response quickly dies down and settles to a relatively low level consistent with the weak employment response.

6 Conclusion

This paper revisits a set of negative results regarding the potential for productivity to be a main driver of labor market fluctuations. We show that both the data and a simple labor search and matching model are consistent with an important role for anticipated productivity shocks. An essential ingredient for a theoretical search and matching model to match the data is a process for wages that falls modestly in response to good news about the future. Empirical wage measures provide support for wages responding in this manner. Furthermore, a simple and plausible model of structural wage determination based on cash flows delivers realistic responses of both quantities and wages.

A natural question, given our assumptions, is how such a wage might be microfounded. One possible foundation can be found in the economic literature that studies the role of sociological/psychological factors such as norms, social consensus, and fairness considerations in wage determination. Our view of wages is close in spirit to the work of Akerlof and Yellen (1990); Akerlof et al. (1996); Bewley (1999); and later Hall (2005), all of whom suggest an important role for such factors in labor markets. Akerlof and Yellen (1990), for example, model a worker's effort on the job as an increasing function of the actual wage relative to some "fair wage," which the authors suggest could depend on a number of factors, including "profits accruing to the firm's owners." Cross-sectional evidence, such as that provided by Dickens and Katz (1987) and Krueger and Summers (1987), also suggests a link between profitability and industry-level wage premia. Moreover, popular media sometimes appear to reflect similar views.[18] While we do not explicitly model the bargaining problem that gives rise to these connections, our work suggests that this would be a fruitful avenue for future research.

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[18]See e.g. www.cbsnews.com/news/corporate-profits-boom-may-lead-to-higher-wages.

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Appendix

A Stationary Representation

The model described in the body of the text is trend stationary with respect to labor-augmenting technological progress, X_t. Denoting detrended variables according to $\tilde{\Delta}_t \equiv \frac{\Delta_t}{X_{t-1}}$ for $\Delta_t \in \{Y_t, C_t, D_t, W_t, K_t, I_t, \phi_t^N\}$ and $\tilde{U}_{C,t} \equiv \frac{U_{C,t}}{X_{t-1}^{-\sigma}}$, and $\tilde{U}_{F,t} \equiv \frac{U_{F,t}}{X_{t-1}^{1-\sigma}}$ we can write the model in terms of only stationary variables:

$$\tilde{Y}_t = \left(\tilde{K}_t\right)^{\alpha} (\gamma_{x,t} N_t)^{1-\alpha} \tag{A.1}$$

$$F_t = N_t + (1 - p_t) S_t \tag{A.2}$$

$$N_t = (1 - \lambda) N_{t-1} + M_t \tag{A.3}$$

$$\tilde{K}_{t+1} = \gamma_{x,t}^{-1} \left[(1 - \delta)\tilde{K}_t + \tilde{I}_t\right] \tag{A.4}$$

$$\tilde{Y}_t = \tilde{C}_t + \tilde{I}_t + \tilde{G}_t + \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right)\gamma_{x,t} V_t \tag{A.5}$$

$$\tilde{D}_t = \tilde{Y}_t - \tilde{W}_t N_t - R_t \tilde{K}_t - \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right)\gamma_{x,t} V_t \tag{A.6}$$

$$1 = E_t \left\{\Omega_{t,t+1}\left[1 - \delta + R_{t+1}\right]\right\} \tag{A.7}$$

$$\tilde{\phi}_t^N = (1 - \alpha)\left(\frac{\tilde{K}_t}{\gamma_{x,t} N_t}\right)^{\alpha} \gamma_{x,t} - \tilde{W}_t + (1 - \lambda) E_t \left\{\Omega_{t,t+1}\gamma_{x,t}\tilde{\phi}_{t+1}^N\right\} \tag{A.8}$$

$$\tilde{\phi}_t^N = \frac{\gamma_{x,t}}{q_t}\left[a_n + \nu\left(\frac{V_t}{V_{t-1}}\right) + \nu'\left(\frac{V_t}{V_{t-1}}\right)\frac{V_t}{V_{t-1}} - E_t\left\{\Omega_{t,t+1}\gamma_{x,t+1}\nu'\left(\frac{V_{t+1}}{V_t}\right)\left(\frac{V_{t+1}}{V_t}\right)^2\right\}\right] \tag{A.9}$$

$$R_t = \alpha\left(\frac{\tilde{K}_t}{\gamma_{x,t} N_t}\right)^{\alpha-1} \tag{A.10}$$

$$-\frac{\tilde{U}_{F,t}}{\tilde{U}_{C,t}} = (1 - p_t)\tilde{\kappa}_t + p_t\left[\tilde{W}_t + (1 - \lambda) E_t\left\{\Omega_{t,t+1}\gamma_{x,t}\left(\frac{1 - p_{t+1}}{p_{t+1}}\right)\left(-\frac{\tilde{U}_{F,t+1}}{\tilde{U}_{C,t+1}} - \tilde{\kappa}_{t+1}\right)\right\}\right] \tag{A.11}$$

$$\tilde{P}_t = \frac{\tilde{Y}_t - R_t\tilde{K}_t - \left(a_n + \nu\left(\frac{V_t}{V_{t-1}}\right)\right)\gamma_{x,t} V_t}{N_t} \tag{A.12}$$

$$\tilde{W}_t = \omega_0 \tilde{P}_t^{\omega^F}\left(\tilde{W}_{t-1}/\gamma_{x,t-1}\right)^{1-\omega^F} \tag{A.13}$$

where $\Omega_{t,t+1} \equiv \beta\frac{\tilde{u}_{c,t+1}}{\tilde{u}_{c,t}}\gamma_{x,t}^{-\sigma}$.

B Steady State and Calibration

We use the restrictions imposed by the deterministic steady state of the model, long-run empirical values for the unemployment rate, $\bar{un} = 0.06$, and the match probability for firms, $\bar{q} = 0.90$, and our value for the ratio of vacancy posting costs to the marginal product of labor, $\Psi^v = 0.17$, to analytically solve for all remaining endogenous variables, as well as χ, a_n, ψ and ω_0.

Note that, because we will choose ψ (which scales the disutility of participation) to satisfy the labor force participation condition, our choice of F is a normalization that has no effect on model dynamics. We may thus proceed with any values of N and F that satisfy $\bar{un} \equiv \frac{F-N}{F} = 0.06$. We choose $\bar{N} = 0.6$ corresponding to a 60% long-run employment to population ratio (and thus a 60% long-run labor force participation rate). Note also that in the steady state, $\nu(V_t/V_{t-1}) = \nu(1) = 0$, so the vacancy posting cost is simply a_n. Below, all variables are detrended, and variables with bars denote values taken from the data.

Since $\Omega = \beta\gamma_x^{-\sigma}$, the Euler equation implies

$$R = \frac{1}{\beta\gamma_x^{-\sigma}} - 1 + \delta. \tag{B.1}$$

Solving the capital demand equation gives

$$K = \bar{N}\gamma_x \left(\frac{R}{\alpha}\right)^{1/(\alpha-1)}, \tag{B.2}$$

which allows us to solve for output $Y = K^\alpha(\gamma_x\bar{N})^{1-\alpha}$. In steady state, job market inflows must equal outflows, so we have

$$M = \lambda\bar{N}. \tag{B.3}$$

The number of searching workers is

$$S = F - \bar{N} + M. \tag{B.4}$$

From this, we obtain p and V using the definition of match probabilities for firms and workers, respectively,

$$p = M/S \tag{B.5}$$

$$V = M/\bar{q}. \tag{B.6}$$

With values for S, V and M, we use the matching function to solve for match efficiency χ,

$$\chi = M/(V^{\epsilon} S^{1-\epsilon}). \tag{B.7}$$

Next, as described in the text, using the definition of Ψ^v—the ratio of vacancy posting costs to the marginal product of labor—we have

$$a_n = \Psi^v (1-\alpha) \frac{Y}{\bar{N}}. \tag{B.8}$$

The vacancy posting condition can then be solved for the wage,

$$W = (1-\alpha) \left(\frac{K}{\gamma_x \bar{N}} \right)^{\alpha} \gamma_x - \frac{a_n \gamma_x}{q} \left[1 - (1-\lambda) \Omega \gamma_x \right]. \tag{B.9}$$

The law of motion for capital and the aggregate resource constraint imply $I = K(\gamma_x - 1 + \delta)$ and $C = Y - G - a_n \gamma_x V - I$.

In the version of the model with the flow wage, the preceding yields a solution for P,

$$P = \frac{Y - RK - a_n \gamma_x V}{\bar{N}} \tag{B.10}$$

giving an implied value of ω_0 of

$$\omega_0 = \left(\frac{W}{P} \right)^{\omega^F} \gamma_x^{1-\omega^F}. \tag{B.11}$$

Finally, the labor force participation condition can be solved for ψ,

$$\psi = \frac{W[(1-p)\kappa + p - (1-\lambda)\gamma_x \Omega (1-p)\kappa]}{\gamma_x \theta F^{\theta-1}[1 - (1-\lambda)\gamma_x \Omega (1-p)]}. \tag{B.12}$$

C Nash Bargaining

Nash bargaining is a common paradigm for wage determination in models of random matching. To investigate how well the model performs under this version of the wage, we solve for the Nash bargained wage implied by our model and then re-estimate the model.

C.1 Solution

The Nash bargained wage satisfies

$$W_t^{NB} = \arg\max_{W_t} [\bar{\mathbf{W}}_\mathbf{t}(W_t) - \bar{\mathbf{U}}_\mathbf{t}]^\eta [\mathbf{J}_\mathbf{t}(W_t) - \mathbf{V}_\mathbf{t}]^{1-\eta}, \tag{C.1}$$

where $\bar{\mathbf{W}}_\mathbf{t}$ denotes the value of a match for the household, $\bar{\mathbf{U}}_\mathbf{t}$ denotes the value of unemployment for the household, $\mathbf{J}_\mathbf{t}$ denotes the value of a match for the firm, and $\mathbf{V}_\mathbf{t}$ denotes the value of a vacancy for the firm. Free-entry of firms implies that $\mathbf{V}_\mathbf{t} = 0$, and our specification of unemployment benefits, combined with the existence of a participation margin for households, implies that $\bar{\mathbf{U}}_\mathbf{t} = \kappa_t$. Thus, the Nash sharing rule reduces to

$$\bar{\mathbf{W}}_\mathbf{t} - \bar{\mathbf{U}}_\mathbf{t} = \left(\frac{\eta}{1-\eta}\right) \mathbf{J}_\mathbf{t}. \tag{C.2}$$

The household match surplus (in units of consumption) may be expressed as the sum of the wage payment earned in the period of the match (due to our timing assumption) and the continuation value of the match, less the lump-sum transfer to the unemployed,

$$\bar{\mathbf{W}}_\mathbf{t} - \bar{\mathbf{U}}_\mathbf{t} = W_t - \kappa_t + (1-\lambda) E_t \left\{ (1-p_{t+1}) \Omega_{t,t+1} (\bar{\mathbf{W}}_\mathbf{t+1} - \bar{\mathbf{U}}_\mathbf{t+1}) \right\}. \tag{C.3}$$

The value of a match to the firm (again, in units of consumption) is given by the current marginal product of the match net of the wage bill plus the continuation value,

$$\mathbf{J}_\mathbf{t} = F_{N,t} - W_t + (1-\lambda) E_t \left\{ \Omega_{t,t+1} \mathbf{J}_\mathbf{t+1} \right\}. \tag{C.4}$$

To solve for the wage associated with Nash bargaining, begin by substituting the expressions for $\bar{\mathbf{W}}_\mathbf{t}$ and $\bar{\mathbf{U}}_\mathbf{t}$ into the Nash sharing rule,

$$W_t^{NB} - \kappa_t + (1-\lambda) E_t \left\{ (1-p_{t+1}) \Omega_{t,t+1} (\bar{\mathbf{W}}_\mathbf{t+1} - \bar{\mathbf{U}}_\mathbf{t+1}) \right\} = \frac{\eta}{1-\eta} \mathbf{J}_\mathbf{t}. \tag{C.5}$$

Iterating the sharing rule forward and substituting in for $\mathbf{\bar{W}_{t+1}} - \mathbf{\bar{U}_{t+1}}$,

$$W_t^{NB} - \kappa_t + (1-\lambda)E_t\left\{(1-p_{t+1})\Omega_{t,t+1}\left(\frac{\eta}{1-\eta}\right)\mathbf{J_{t+1}}\right\} = \frac{\eta}{1-\eta}\mathbf{J_t}. \tag{C.6}$$

Replacing $\mathbf{J_t}$ with the firm's first-order condition for labor and using $\mathbf{J_{t+1}} = \phi_{t+1}^N$,

$$\begin{aligned} W_t^{NB} - \kappa_t + (1-\lambda)E_t\left\{(1-p_{t+1})\Omega_{t,t+1}\left(\frac{\eta}{1-\eta}\right)\phi_{t+1}^N\right\} \\ = \frac{\eta}{1-\eta}\left(F_{N,t} - W_t^{NB} + (1-\lambda)E_t\left\{\Omega_{t,t+1}\phi_{t+1}^N\right\}\right). \end{aligned} \tag{C.7}$$

Solving for W_t^{NB}, we obtain

$$W_t^{NB} = (1-\eta)\kappa_t + \eta\left[F_{N,t} + (1-\lambda)E_t\left\{\Omega_{t,t+1}p_{t+1}\phi_{t+1}^N\right\}\right]. \tag{C.8}$$

The stationary representation used for estimation is obtained by dividing through by X_{t-1}, which yields

$$\tilde{W}_t^{NB} = (1-\eta)\tilde{\kappa}_t + \eta\left[\tilde{F}_{N,t} + (1-\lambda)\gamma_{x,t}E_t\left\{\Omega_{t,t+1}p_{t+1}\tilde{\phi}_{t+1}^N\right\}\right]. \tag{C.9}$$

C.2 Calibration

Our calibration strategy, described in Section 4 and Appendix B, pins down all endogenous variables and parameters in the steady state version of (C.9), except for η, the bargaining share parameter. Accordingly, to ensure that our long-run restrictions are satisfied, we choose η to solve (C.9), given the steady state values we compute above:

$$\eta = \frac{(1-\kappa)}{\frac{F_n + (1-\lambda)\gamma_x\Omega p\gamma_x a_n/q}{W} - \kappa}. \tag{C.10}$$

C.3 Estimation and results

We estimate the model under Nash bargaining in the same way we estimate the model under the flow wage. In particular, we allow the data to choose between the model and a simple inertial wage rule:

$$W_t = (W_t^{NB})^{\omega^{NB}} W_{t-1}^{1-\omega^{NB}}. \tag{C.11}$$

Table 5 reports the parameter estimates from our estimation of the model with Nash

Table 5: Parameter Estimates (Nash bargaining)

Parameter	**Concept**	**Estimate**
θ	Labor supply elasticity	10.000
σ	Inv. intertemporal elasticity	0.500
ξ	Vac. posting cost (curvature)	0.056
ϵ	Matching function elasticity	0.950
ω^{NB}	Nash Term	0.500

bargaining. We immediately see that the parameter estimates are all hitting their bounds with the exception of ξ.[19] Most notably, ω^{NB}—the parameter that governs the relative strengths of the inertial and Nash components of the wage in (C.11)—is at its lower bound of 0.5. This indicates that the data unambiguously prefer an inertial wage to the Nash bargained wage. Put differently, the model with Nash bargaining would perform even worse if we were to impose $\omega^{NB} = 1$, thus insisting that Nash bargaining hold exactly.

Figure 12 reports the empirical and model-based impulse responses to our identified shock. Not surprisingly in light of the results in Table 5, the model with Nash bargaining cannot generate the magnitude of responses that we observe in the data, especially in the period of anticipation. In fact, output, consumption and investment each *fall* during the anticipation period, whereas all three series rise strongly in the data.

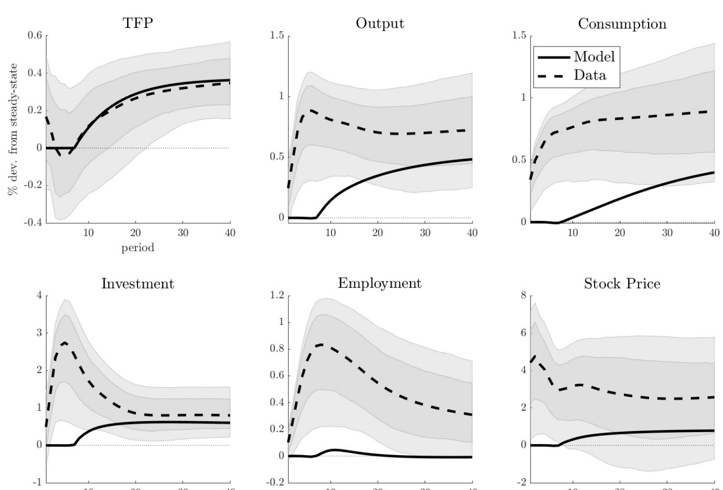

Figure 12: Estimated model with Nash bargained wage

[19]Because our point estimates are all hitting bounds, the corresponding standard errors are invalid, so we do not report them.

As we discuss in the text, the model with Nash bargaining is unable to account for the data because the Nash-bargained wage is fundamentally forward-looking: A boom in employment and consumption today will increase the present discounted value of a match, thus driving up the Nash bargained wage and precluding the original rise in employment and consumption. This negative feedback thus chokes off any substantial response under Nash bargaining during the anticipation period, a result which bears out in Figure 12.

D Data Sources and Construction

Our main VAR specification consists of TFP, output, consumption, investment, employment, and the stock price. Except when otherwise noted, we download these series from the FRED database of the St. Louis Federal Reserve Bank.

For TFP, we use the capacity utilization adjusted measure described by Basu et al. (2006) and downloaded from https://www.frbsf.org/economic-research/indicators-data/ on June 1, 2019. To compute the level of TFP we cumulate the growth rates starting from the initial observation in 1947Q2.

Quantity variables are provided in real per-capita terms. Our population series is the civilian non-institutional population ages 16 and over, produced by the BLS. We convert our population series to quarterly frequency using a three-month average and smooth it using an HP-filter with penalty parameter $\lambda = 1600$ to account for occasional jumps in the series that occur after census years and CPS rebasings (see Edge and Gürkaynak (2010)). Our deflator series is the GDP deflator produced by the BEA national accounts.

For output, we use seasonally adjusted nominal output produced by the BEA divided by the population and the GDP deflator. For investment, we take the sum of nominal gross private domestic investment and personal expenditures on durable goods, again divided by the population and the GDP deflator. Consumption consists of nominal personal consumption expenditures on non-durables and services, also divided by the GDP deflator and population. Our measure of employment is total non-farm payroll employment from the BLS's Current Establishment Survey (CES) and is also divided by the population. Lastly, our measure of real stock prices is based on the NYSE index from the Center for Research in Security Prices (CRSP) and is deflated by the GDP deflator and divided by the population.

Our set of auxiliary variables $\mathbf{W}_t$ includes 19 measures of aggregate and sectoral wages. Our preferred wage measure comes from the BEA National Accounts, series code A132RC, and consists of wage and salary compensation for private industries. To arrive at an hourly wage, we divide this by total private sector hours from the BLS Labor Productivity and Costs release (Nonfarm Business Sector: Hours of All Persons) and the GDP deflator.

The additional elements of the wage panel include: (i) median weekly earnings divided by the GDP deflator from the BLS's Current Population Survey, (ii) the new hire real wage series produced by Basu and House (2016) and downloaded from https://www.nber.org/data-appendix/w22279/, and (iii) sixteen additional hourly wage series originating from the super-sector classification level of the CES. These series are listed in Table 6. We download each

Table 6: CES Sectoral Wage Series

Sector	Code
Total Private	AHETPI
Goods Producing	CES0600000008
Mining	CES1000000008
Manufacturing	CES3000000008
Services	CES0800000008
Trade, Transportation, and Utilities	CES4000000008
Wholesale Trade	CES4142000008
Retail Trade	CES4200000008
Transportation and Warehousing	CES4300000008
Utilities	CES4422000008
Information	CES5000000008
Financial Activities	CES5500000008
Professional and Business Services	CES6000000008
Education and Health Services	CES6500000008
Leisure and Hospitality	CES7000000008
Other Services	CES8000000008

from the FRED database in nominal terms and then divide by the GDP deflator to arrive at real hourly wages.

Other labor market responses are constructed by adding a set of standard series to $\mathbf{W}_t$. The vacancies series is taken from Barnichon (2010), which splices together measures of print and online help-wanted advertising. Labor force participation is the Civilian Labor Force Level, produced by the BLS, divided by the same population series used to construct our other per-capita measures. Our hours series is the BLS's Hours Worked for All Employed Persons in the Nonfarm Business Sector. The unemployment series is the standard measure constructed by the BLS.

Finally, we consider two measures of the job-finding probability. The first is based on monthly unemployment data, and is constructed as

$$JFP_t^1 \equiv \frac{U_{t-1} - (U_t - U_t^{st})}{U_{t-1}} \tag{D.1}$$

where U_t is the total number of unemployed workers in period t and U_t^{st} is the total number of short-term (less than 5 weeks) unemployed workers. We construct the monthly series for JFP_t^1, and then compound the monthly probabilities over three months to get quarterly job-finding probabilities. Our second job-finding probability series is based on the JOLTS survey, and only exists for the post-2000 sample. We construct it as

$$JFP_t^2 \equiv \frac{NH_t}{U_t + NH_t} \tag{D.2}$$

where NH_t is the gross number of newly hired workers. The timing in this formula is designed to be consistent with our assumption that workers begin work in the same period they are hired.

E Additional Results and Robustness

E.1 Variance Decomposition

Table 7 reports the variance decomposition of our identified shock in the time domain.

Table 7: Variance decomposition of VAR variables (time domain)

Horizon	TFP	Y	C	I	N	NYSE
0	0.06	0.17	0.69	0.06	0.22	0.30
4	0.02	0.62	0.86	0.55	0.61	0.35
8	0.02	0.72	0.91	0.57	0.66	0.36
12	0.04	0.78	0.93	0.59	0.68	0.38
16	0.07	0.82	0.94	0.60	0.69	0.39
20	0.12	0.84	0.95	0.61	0.70	0.39
40	0.36	0.88	0.95	0.65	0.67	0.41
80	0.63	0.91	0.95	0.69	0.64	0.53
200	0.78	0.90	0.92	0.72	0.62	0.67

The identified shock explains over 60% of both output and employment at short horizons (by one year), and explains at least this much of both variables at all longer horizons. On the other hand, the shock only explains a small fraction of TFP (less than 10%) at horizons under five years, but thereafter explains an increasingly large fraction of TFP, ultimately growing to nearly 80%. These patterns are consistent with the notion of "technological diffusion news" that our procedure is designed to identify and indeed are similar to the results in Portier (2015).

E.2 Empirical Exercise

Our empirical impulse responses are robust to (i) changing the number of lags in the VAR, (ii) running a VECM imposing one, two, or more trends in the data, (iii) expanding the set of observables in $\mathbf{Y}_t$ to include additional variables, such as alternative labor market indicators, and (iv) changing the sample period used for estimation.

For example, restricting the sample to start in 1985—a common alternative start date in the VAR literature—delivers qualitatively similar responses for all variables. We plot these responses in Figure 13.

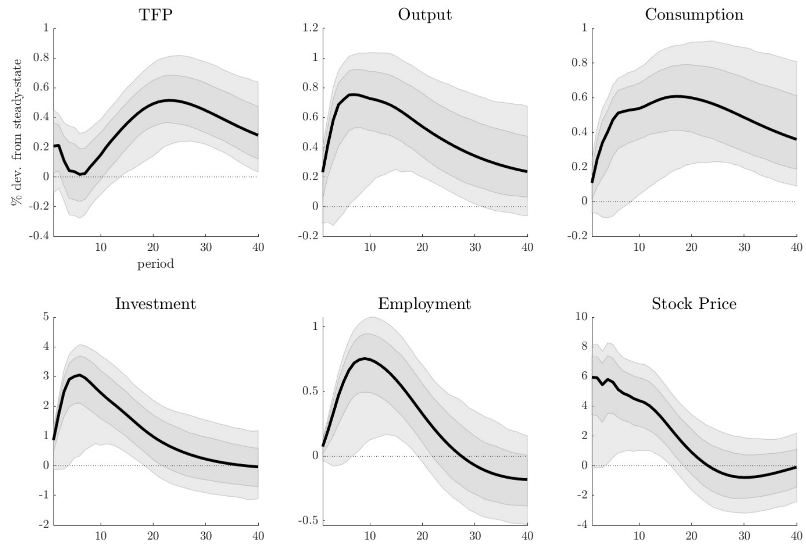

Figure 13: VAR impulse responses for the short sample starting in 1985Q1

E.3 Suitability

Several authors have observed that, under some circumstances, VAR strategies may not be applicable to identify shocks. In particular, in some models, current and past observables may not span the space of past economic shocks, in which case static rotations of reduced-form residuals cannot correspond to the underlying economic shocks.

To address this concern, we consider our estimated baseline flow-wage model with anticipated permanent and unanticipated temporary TFP shocks as calibrated above, and extend it to include four additional shocks: (i) shocks to matching efficiency via stochastic fluctuations in χ, (ii) shocks to labor supply via stochastic fluctuations in ψ, (iii) shocks to demand via stochastic fluctuations in β, and (iv) government spending shocks. We calibrate these additional shocks such that each drives a substantial portion of business cycle variation in at least one variable in our data set. Table 8 reports the corresponding variance decomposition of the theoretical model between two and 500 quarters. Importantly, surprise and anticipated TFP shocks each account for roughly half of total variation in TFP in the model.

We then apply our exact empirical procedure to data simulated from the model, first a single extremely long sample and then 2,000 samples of the same length as our baseline data sample. This test thus accounts for functional form restrictions (i.e. 4 lags in the VAR) and finite sample bias that might appear in our estimates. Figure 14 shows that the procedure recovers the theoretical impulse responses quite well, though not surprisingly responses are

Table 8: Variance decompositions of theoretical variables

Shock	**TFP**	**Y**	**C**	**I**	**N**	**NYSE**
Matching	0.00	0.09	0.09	0.08	0.13	0.07
Gov. Spending	0.00	0.03	0.13	0.02	0.04	0.04
Labor Supply	0.00	0.07	0.07	0.08	0.11	0.06
Discount Factor	0.00	0.11	0.13	0.16	0.12	0.11
Surprise TFP	0.53	0.15	0.13	0.21	0.10	0.13
News TFP	0.47	0.55	0.45	0.44	0.51	0.60

downward biased in the finite sample. For comparison, the figure also displays the average response that would be estimated on the same samples using the Kurmann and Sims (2020) approach to identifying news; these responses demonstrate a much larger impact change in TFP and a much stronger downward bias in the estimated response of employment, consistent with patterns we observe in the actual data.

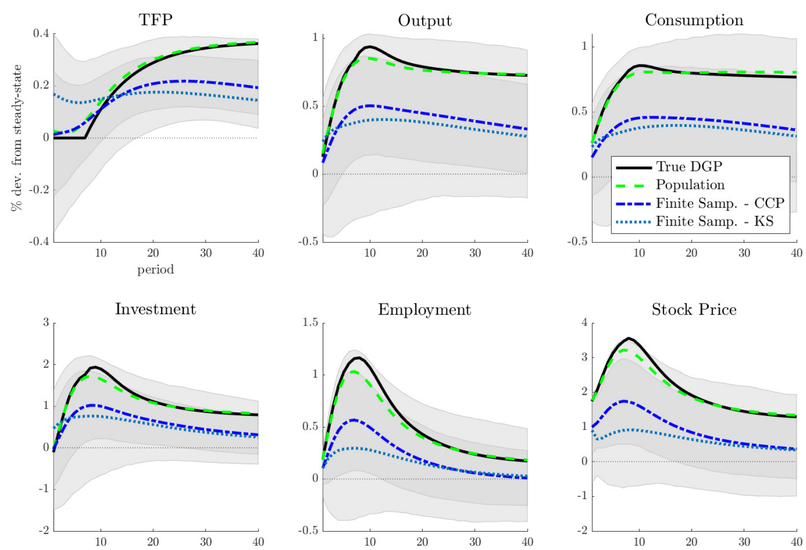

Figure 14: Suitability exercise of empirical approach using simulated data. Dashed lines show point estimates from one 20,000 period sample. Dotted-dashed lines show the mean estimated response from 2,500 simulated samples of T=212 periods using our identification strategy. Dotted lines show the corresponding object for the Kurmann and Sims (2020) identification strategy. Bands show the 68% and 90% interval of estimated responses from among the 2,500 model simulations.