Anticipated Productivity and the Labor Market*

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Abstract

We identify the main shock driving comovement of the labor market with output. The shock induces business cycle patterns in output, consumption, investment, hours, and stock prices and is orthogonal to business cycle fluctuations in TFP. Yet, the shock is associated with future TFP fluctuations, consistent with theories of technology news. 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 TFP news. The response of the wage implied by this rule is consistent with a broad panel of wage series.

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 revisit the question of what causes labor market fluctuations. Our objective is to study this question without making strong prior commitments regarding two of the most controversial elements in macroeconomic models of the labor market: (i) the fundamental disturbances causing fluctuations; and (ii) the mechanism by which wages propagate disturbances through the labor market. To this end, the paper begins with a simple empirical VAR exercise, in which we identify in an agnostic way the "main" shock driving joint fluctuations in output and hours. The shock we uncover drives significant business cycle frequency fluctuations in standard macroeconomic aggregates, including hours, but only small and statistically insignificant fluctuations in both inflation and 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 a classic news shock.

Taken together, the 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. We therefore ask if 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 a search friction in the labor market and Greenwood et al. (1988) preferences to our estimated impulse responses.

A distinctive feature of our approach to modeling the labor market is that we do not initially impose a particular structural model of wage determination. Instead, we once again remain agnostic, and 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. 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 wage process to propose a parsimonious model of wage determination that fits the data nearly as well as the reduced-form process.

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 align 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? It turns out 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 flow after accounting for payments to capital and the costs of hiring. This model of wage setting 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 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, all but four fall on impact according to our point estimates, and none are significantly positive. Second, virtually all of the wage series exhibit upward-sloping patterns in the period 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, total employment, unemployment, and job finding probabilities.

Our results 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. We also show that the main features of the shock could be recovered via an identification procedure that seeks to explain the maximal variation in future forecast revisions of TFP. In this respect, our agnostic identification procedure recovers the same shock that is recovered by a common approach that has been specifically designed to isolate news shocks.

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. This result contrasts with some recent findings in the literature. In particular, though our methodology is similar to Angeletos et al. (2020), they find that TFP cannot be the "main business cycle" shock. The crucial difference between our respective approaches is that, in their identification procedure, Angeletos et al. (2020) specifically target narrow portions of the spectrum, focusing on business cycle fluctuations between 6 and 32 quarters in the frequency domain, while our procedure targets both business-cycle and longer-run fluctuations.[1]

Our empirical results are also related to a long literature seeking to identify news shocks in VARs, notably 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 fact, our main empirical results are recovered if we employ the identification approach of Kurmann and Sims (2020), who seek to identify the shock that best explains forecast revision in TFP in the distant future. Nevertheless, our empirical exercises give somewhat different results and our focus on the cyclicality of real wages and theories of wage determination is quite different

[1] Our baseline targets fluctuations with periodicities between 6 and 500 quarters, but our results do not depend on going out this far. As the top of this range shrinks below 100 quarters, the identified responses gradually change to look more like those in Angeletos et al. (2020).

from theirs.[2]

Recently, Faccini and Melosi (2020) have estimated a structural labor search model with sticky wages, and also 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-setting 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 provide 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.

This paper proceeds as follows. In Section 2, we describe our main empirical exercise aimed at identifying the shock that drives the covariance of output and hours. Section 3 describes a theoretical labor search model with an anticipated productivity shock. Section 4 estimates the parameters of the model needed to match our estimated impulse responses and discusses the implications of the estimation exercise for a plausible model of wage determination, as well as the relation with empirical measures of the wage and several other labor

[2]When we use the shock identified by Kurmann and Sims (2020) on our sample period (i.e. through 2018Q4), hours rise. However, when we instead use their sample period (i.e. through 2007Q3), hours do not always rise on impact. Our approach consistently gives a positive impact for hours across sample periods and specifications.

market variables. Section 5 argues that a flow-based surplus sharing model of the wage can fit the data well. Section 6 concludes.

2 Empirical Exercise

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 estimated residuals, $\mu_t \equiv A\epsilon_t$.

We take as our baseline set of variables $\mathbf{Y}_t \equiv [TFP_t, GDP_t, C_t, I_t, H_t, SP_t]'$, which includes utilization-adjusted TFP from Fernald (2014), real per-capita GDP, real per-capita consumption, real per-capita investment, per-capita hours, 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 1966Q1 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, and two measures of technological innovation. These series are related to current and past observations of $\mathbf{Y}_t$ according to

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

where the coefficient matrix $\Gamma(L)$ 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 auxiliary wage measure in $\mathbf{W}_t$ using the responses of the variables $\mathbf{Y}_t$ and the estimated values of $\Gamma(L)$.

2.1 Identification Approach

Our objective is to understand the source of comovement between the labor market and other real variables. To do this, we employ a procedure 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 the largest portion of the covariance between output and hours in our data.

Our approach to identification is motivated by two primary considerations. First, we want to explore the empirical patterns that have historically been of most interest to researchers, and finding the cause of joint fluctuations in output and hours remains a central focus of the macro-labor literature. Second, we wish to avoid pre-judging the nature of the economic shocks behind these fluctuations.[3] If a single shock does drive a large portion of this comovement, then our approach is likely to isolate the effects of that shock quite well and allows us to identify salient features of other timeseries, including productivity, that are associated with the joint fluctuations in our target variables.

Like Angeletos et al. (2020), we target a moment extracted from the frequency domain, but our target is different in two respects. First, we target the covariance matrix of output and hours, rather than targeting a single variable (e.g. output only) at a time. In this respect, we are explicitly directing our procedure to identify the shock that drives comovement between output and the labor market. Second, we target a wider band of frequencies than do Angeletos et al. (2020), who attempt to isolate the sources of business cycle comovements from the sources of comovements at either shorter or longer periodocities.

Specifically, define

$$\phi(z) \equiv (I - B(z))^{-1} A \tag{3}$$

as the z transfer-function associated with the MA-infinity representation of equation (1). Further, let s be a matrix selecting the target variables of interest. In our baseline case, $s = [e_2, e_5]'$, where e_i is the i^{th} column basis vector. The covariance associated with spectra of periodicity $p \equiv [p_1, p_2]$ is given by

$$\Sigma_p^s \equiv \frac{1}{2\pi} \int_{2\pi/p_2}^{2\pi/p_1} \left[s\phi(e^{-i\lambda}) \right] \left[s\phi(e^{i\lambda}) \right]' d\lambda. \tag{4}$$

Conversely, the contribution of each shock to the variance in the same range is given by

$$\Omega_p^s \equiv \frac{1}{2\pi} \int_{2\pi/p_2}^{2\pi/p_1} \left[s\phi(e^{-i\lambda}) \right]' \left[s\phi(e^{i\lambda}) \right] d\lambda. \tag{5}$$

[3] Our approach does not, for example, make any assumption that the fluctuations we uncover are related to productivity, in contrast to most of the literature on News shocks.

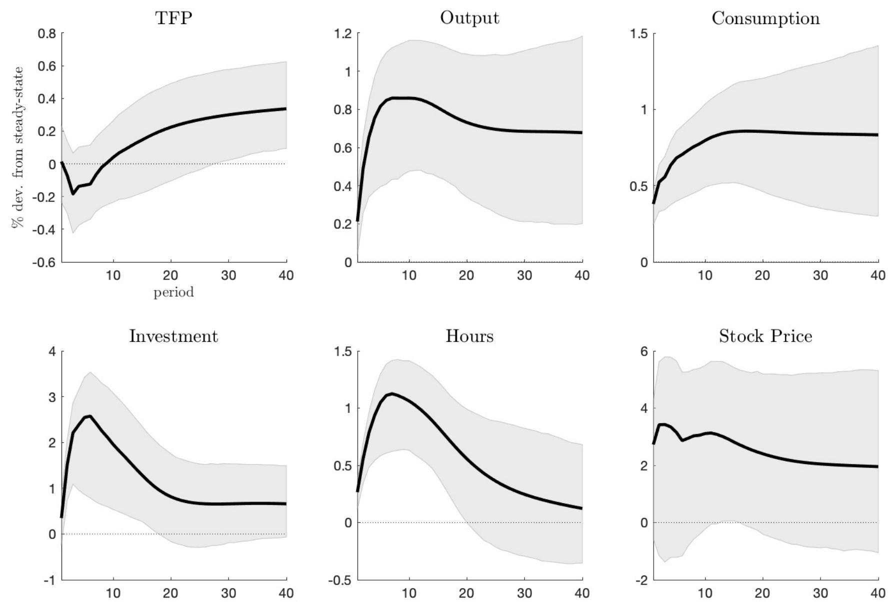

Figure 1: Impulse responses to identified shock.

We can then find the shock that explains the most of Σ_p^s by computing q_1, the eigenvector associated with the largest eigenvalue of Ω_p^s and setting

$$A = \hat{A} q_1, \tag{6}$$

where $\hat{A}$ is the Cholesky decomposition of the matrix $\Sigma_u \equiv \mathrm{cov}(\mu_t)$.

In contrast to Angeletos et al. (2020), we consider a wider range of spectra, with periodicity $p = [6, 500]$ quarters, because we do not want to impose an *ex ante* separation between the shocks that drive the business cycle and those that drive longer-run fluctuations. In practice, this is little different from considering unconditional covariances, but it has the advantages of (i) excluding extremely short-range fluctuations that might be associated with, e.g., measurement error, and (ii) remaining feasible even if the estimated process has a unit root and unconditional variances are not defined, as would occur should we have estimated (1) as a VECM.

2.2 Results

Figure 1 presents the impulse responses to our identified shock, along with 80% confidence bands from a bias-corrected bootstrap. The figure shows that our shock drives large and

Table 1: Variance decompositions of VAR variables

Frequency (Quarters)	**TFP**	**Y**	**C**	**I**	**N**	**S&P**
Business Cycle (6-32)	0.111	0.386	0.634	0.358	0.493	0.161
Medium run (32-100)	0.149	0.620	0.776	0.467	0.648	0.139
Long run (100-500)	0.551	0.783	0.795	0.703	0.681	0.249

significant immediate fluctuations in output, consumption, investment and hours, as well as a substantial though marginally significant response 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.

Central for our insights in this paper is the response of utilization-adjusted TFP, our preferred measure of production technology. On impact of the shock, TFP is unchanged and then falls modestly (and insignificantly) for several quarters, before it begins a gradual rise that becomes statistically significant after roughly seven years. This pattern of productivity is consistent with the idea of a "news" shock. Indeed, the response of TFP identified here closely resembles the "technology diffusion" pattern emphasized by Portier (2015) in his comment on Barsky et al. (2015). It is this interpretation that we explore in the following sections.

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 (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 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 periods 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 wages, we produce impulse responses for a number of empirical wage measures to our identified shock. These wage responses are

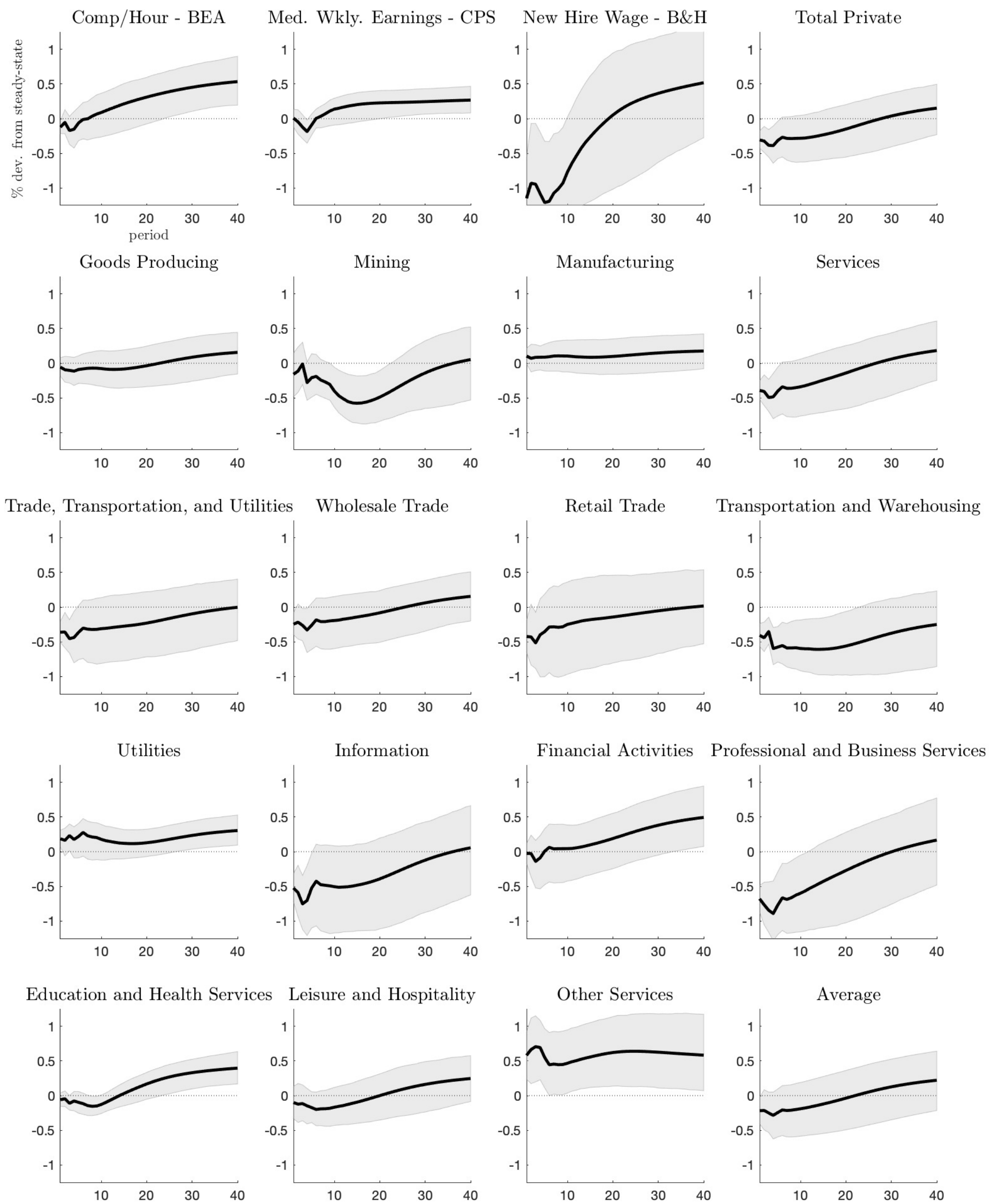

Figure 2: Wage responses to labor market shock.

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, all but four fall on impact, none is significantly positive, and nearly all of the series appear to grow over the horizon of the response.

Apparently, the data suggest that a productivity news shock could potentially play a central role in driving business cycle fluctuations, as well as longer-term changes in macroeconomic aggregates. Standard models, however, will have trouble rationalizing these patterns. Real models with flexible prices will not generally be able to produce an expansion during the anticipation period. By contrast, new-Keynesian models with sticky prices can explain the expansion during the anticipation period, but will generally cause TFP improvements to be contractionary for labor when they are realized (Basu et al., 2006). In the next sections, we explore the ability of a real model with a non-standard specification of the wage to account for our empirical results.

2.3 Further Evidence of News

To verify that we have identified a news shock, we consider several additional pieces of evidence.

2.3.1 Relationship to News Shock Procedure

One advantage of our approach to identifying a shock using the comovement of output and hours is that we do not commit *ex ante* to any particular interpretation of the shock. Given our finding that our identified shock closely resembles a news shock, however, it is natural to ask if we would have found the same impulse responses had we used a more standard approach to identifying news.

The answer, it turns out, is yes. In Appendix E, we present impulse responses for our baseline shock and for the long-horizon identification procedure used by Kurmann and Sims (2020). As the figure in the appendix shows, we find impulse responses that are extremely similar to the news responses that their alternative procedure identifies. We read this evidence as corroborating our interpretation that the shock we identify is, in fact, a

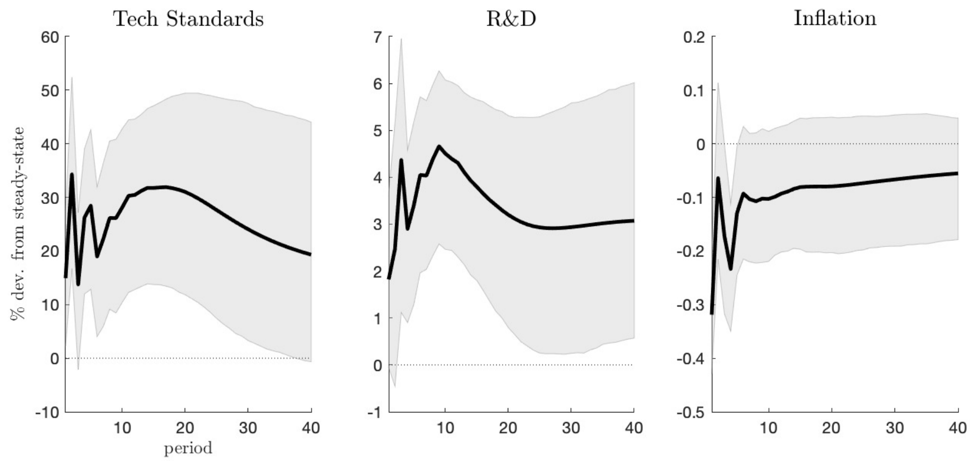

Figure 3: Measures of technological innovation and inflation.

news shock.

2.3.2 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. 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." 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.

The first two panels of Figure 3 report impulse responses of the two new variables to the shock we have identified. The left-most panel indicates that the index of technological standards rises substantially and statistically significantly on impact of the shock, and remains significantly elevated for the majority of the 40-quarter horizon. The center panel indicates that the response of R&D expenditures is more muted on impact—rising, but not significantly—and only becomes significantly positive after several quarters. Thus, the rise in the standards index appears to slightly lead the rise in R&D, while both series rise well before the eventual rise in adjusted TFP. This pattern of responses is consistent with our interpretation that our shock reflects news about future productivity: If the shock we identify were, for example, a shock to the R&D sector, we would expect the increase in the standards index to *lag* the increase in R&D expenditures, with both rising prior to the rise in adjusted TFP.[4]

Finally, the right-most panel of Figure 3 also shows the response of inflation to our identified shock. The point estimate is negative, and is generally not significant, suggesting that the pattern of fluctuations induced by our shock is not consistent with pure monetary shocks or with other standard new-Keynesian types of demand shocks. This finding is also similar to Kurmann and Sims (2020), although those authors find a somewhat larger fall in inflation.

2.4 Summing Up

The evidence above strongly suggests a news interpretation of the shock we have identified. Indeed, a leading identification strategy designed to capture news delivers nearly identical conclusions. Our approach in the remainder of the paper is therefore to ask: How far can the news hypothesis go in explaining the empirical patterns we have isolated? While other shocks could potentially play a part in driving the dynamics we have uncovered, our analysis below shows that our empirical findings are consistent with technological news playing the central role in driving output and labor market fluctuations.[5]

A key challenge for the news story is that it is difficult to get hours 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 high inflation during the periods of anticipation of the future increase in productivity.

[4] Figure 1 in Baron and Schmidt (2017) is instructive on the relevance of the sequencing of events in technological advance.

[5] In Appendix 4.2, we show that our identification approach works to identify news even when other shocks are present in the true data generating process.

Labor-search models offer one natural way to circumvent these two challenges: 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 hours 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-setting 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).

3.1 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.[6]

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. Moreover, 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.[7] Each period, previously productive

[6]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.

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

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

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

The household takes the rental rate of capital, the 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 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,

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

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

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

where a_n, the cost of posting a vacancy, 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 yield the vacancy posting condition

$$\frac{a_n X_t}{q_t} = F_{n,t} - W_t + (1-\lambda)E_t\left\{\Omega_{t,t+1}\frac{a_n X_{t+1}}{q_{t+1}}\right\}. \tag{18}$$

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

$$V_t^{firm} = (Y_t - W_t N_t - R_t K_t - a_n X_t V_t) + E_t\left\{\Omega_{t,t+1}V_{t+1}^{firm}\right\}. \tag{19}$$

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,

$$\Delta SP_t \equiv (\Delta V_t^{firm})^{\phi_{lev}}. \tag{20}$$

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:

$$\tau_t = G_t + (1-p_t)S_t\kappa_t. \tag{21}$$

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.

$$G_t = G_{t-1}\gamma_{x,t-1}. \tag{22}$$

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" wage, which places essentially no *a priori* structure on how wages can respond to shocks. In particular, we model wage growth as an MA(H) process augmented with an error-correcting term designed to ensure that the wage eventually returns to its long run level. Specifically, we assume

$$\Delta w_t = \gamma(L)\epsilon_t - \phi_x(w_{t-1} - x_{t-1}), \tag{23}$$

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,

$$M_t = \chi V_t^{\epsilon} S_t^{1-\epsilon}. \tag{24}$$

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,

$$U(C_t, F_t) = \frac{\left(C_t - \psi X_t F_t^{\theta}\right)^{1-\sigma}}{1-\sigma}. \tag{25}$$

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

$$F(K_t, X_t N_t) = K_t^{\alpha}(X_t N_t)^{1-\alpha}. \tag{26}$$

Table 2: Calibrated Parameters

Parameter	Concept	Value
β	Discount factor	0.990
σ	Inv. intertemporal elasticity	1.500
α	Capital share	0.320
δ	Depreciation rate	0.030
λ	Separation rate	0.120
ψ	Preference parameter	1.359
κ	Replacement rate	0.200
a_n	Vacancy posting cost	0.295
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)	0.900
σ_x	TFP growth (innov std. dev.)	0.050

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

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 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%. The value $\sigma = 1.5$ corresponds to a standard calibration of the intertemporal elasticity. 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.[8]

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

$$-\frac{U_{F,t}}{U_{C,t}} = W_t \left[p_t + (1 - p_t)\kappa\right] \tag{27}$$

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 $\sigma_x = 0.05$, $\rho_x = 0.90$, and $h = 9$.

As a final parameter, we need to fix a_n, the 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 0.301 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 85% 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 via a standard impulse response matching exercise, where 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.[9] Because we aim to match 40 periods, we fix the horizon of the MA terms in the wage process at $H = 40$.

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

[9] 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.

Table 3: Parameter Estimates (Agnostic Wage)

Parameter	Concept	Estimate	Std. Err.
θ	Labor supply elasticity	6.265	2.242
ϵ	Matching function elasticity	0.818	0.031

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

$$\mathcal{L}(\Theta) = (\hat{\psi} - \psi(\Theta))' W (\hat{\psi} - \psi(\Theta)) \tag{28}$$

where $\Theta \equiv \{\theta, \epsilon, \gamma_0, \gamma_1, ...\gamma_H\}$ is the vector of parameters we seek to estimate and W is a diagonal matrix consisting of the inverse of the bootstrapped variances of each entry in $\hat{\psi}$.[10]

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.2. There, we augment our model with four 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 two 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

[10]Estimating the agnostic wage process occasionally delivers "jagged" responses near the end of the impulse response horizon. For this reason, we augment the loss function (28) 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.

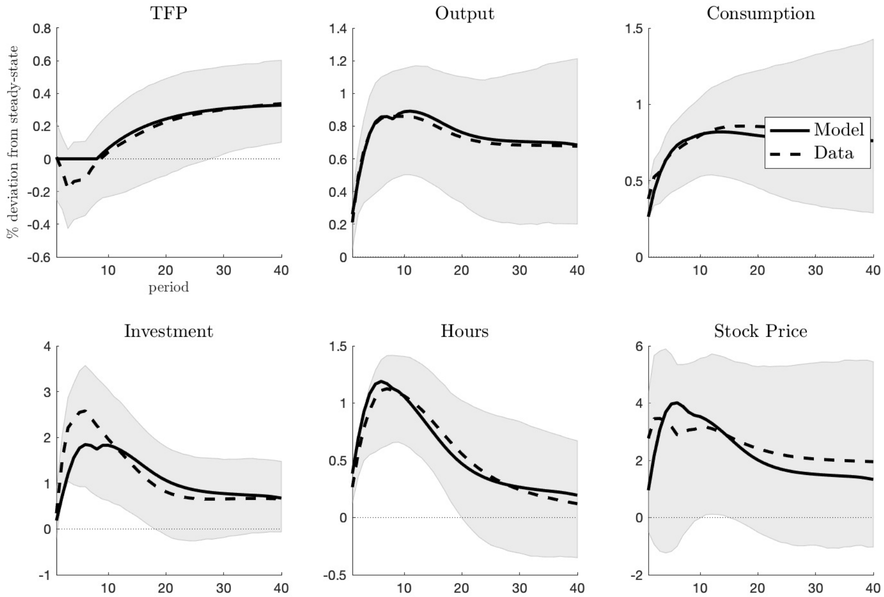

Figure 4: Quantity responses: Model (agnostic wage) and data

literature.[11]

Figure 4 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 excellent. The model almost exactly matches the impact effect, as well as the subsequent trajectories, of output and hours in the data. The response of the stock price is somewhat muted on impact relative to the data, but quickly catches up as investment and employment rise. Investment, in turn, rises less quickly in the model than in the data, but subsequent dynamics are similar.

Figure 5 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, all but four of the series fall on impact, and all but two of the series 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

[11]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).

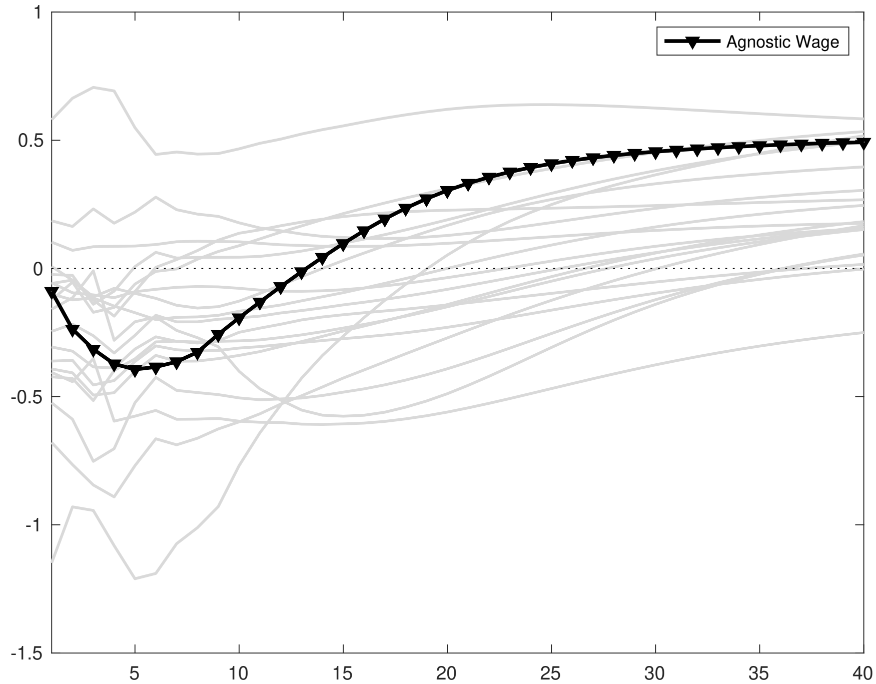

Figure 5: Wage response: Model (agnostic wage) and data

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 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.

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 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 our semi-structural exercise.

5 A 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 and 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 this intuition, a natural alternative is a sharing rule based on the *flow* match surplus, 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 flow 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). In particular, we consider a model in which wages are given by

$$W_t = \omega_0 P_t \tag{29}$$

where

$$P_t \equiv \frac{Y_t - R_t K_t - a_n X_t V_t}{N_t}. \tag{30}$$

This process embodies the qualitative features towards which our estimated agnostic wage process pointed. 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.[12]

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

[12]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	2.366	0.144
ϵ	Matching function elasticity	0.709	0.005
ω^F	Flow term	0.658	0.004

implied dynamics of quantities 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 (29) intended to allow the data to choose between our model and a simple inertial wage rule:

$$W_t = \omega_0 P_t^{\omega^F} W_{t-1}^{1-\omega^F} \tag{31}$$

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, 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 elasticity of the matching function with respect to vacancies, ϵ, and a significantly lower elasticity of labor supply, θ.

Figure 6 plots the impulse responses from our empirical identification procedure against those implied by our simple model of wage setting. Despite the fact that we now have 40 fewer degrees of freedom, the model fit remains excellent. Observationally, there is little difference between Figures 4 and 6, while the minimized value of the criterion has increased only marginally despite the parsimony of the model—both in terms of the underlying search

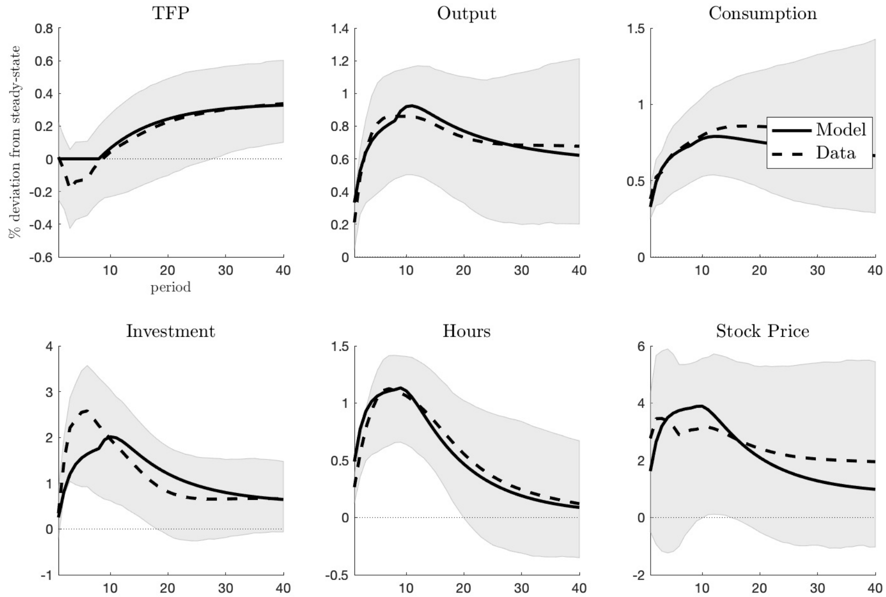

Figure 6: Quantity responses: Model (flow wage) and data

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 setting model, Figure 7 plots the response of both estimated wages 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 hours that we observe in the data.

5.2 Flow Wage: Critical Features

The empirical success of our simple 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, expec-

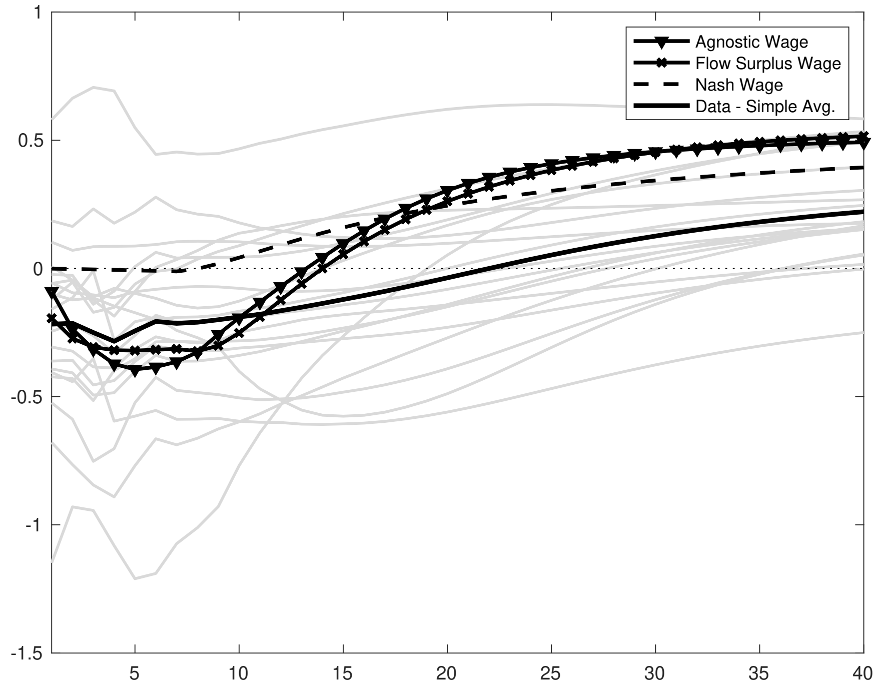

Figure 7: Estimated wage responses in data and model.

tations about higher future productivity increase the incentive for firms to post vacancies ahead of 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 the current period's surplus—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.

Importantly, we estimate a value of 0.66 for ω^F, the weight on the flow wage process, implying 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 don't 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 doesn't occur, leaving no initial increase in vacancy posting for the flow wage processes to amplify.

In 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 traditional 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 traditional productivity shocks.[13] 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.

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, the Beveridge curve, and labor's share of income.

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

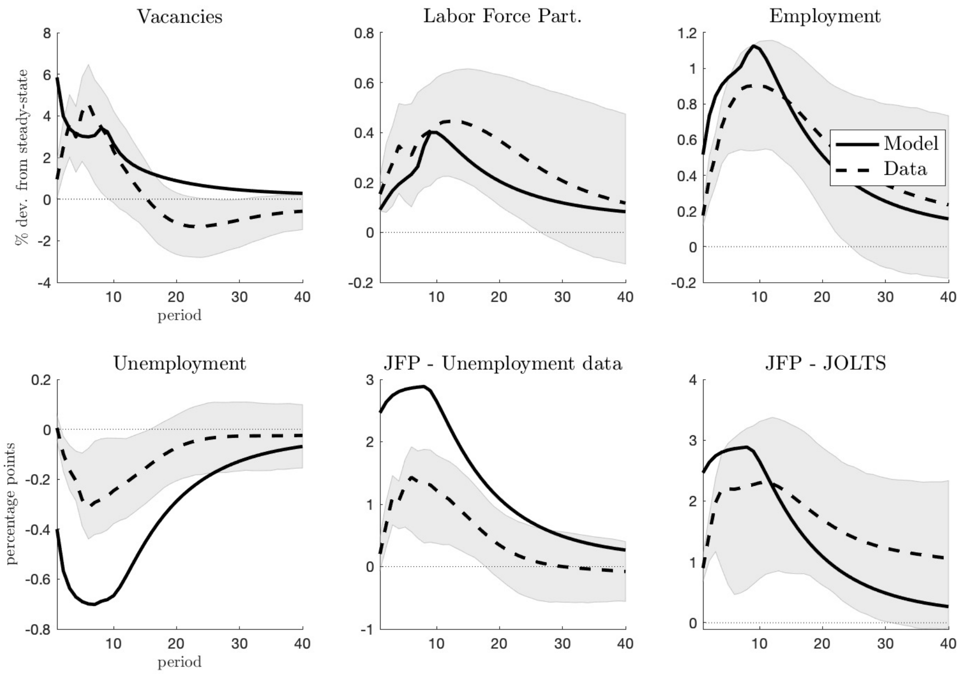

Figure 8: Labor market variables

5.3.1 Labor Market Variables

We have demonstrated that our parsimonious model provides a remarkably strong account of the quantity data used in estimation. If the mechanism we propose is, in fact, important for explaining labor market fluctuations, we should also expect the model to be at least broadly consistent with other labor market indicators that we did *not* target in our estimation. Thus, to evaluate our model's out-of-sample fit, Figure 8 plots impulse responses of five key labor market variables—vacancies, labor force participation, employment, unemployment, and two measures of the job-finding rate—in our estimated model and in the data.

We view the results in Figure 8 as supportive of the mechanism we describe and our main conclusions. The responses of vacancies, labor force participation and employment in our model are all broadly consistent with the empirical responses. Unemployment and the job-finding probability in the model move too much on impact relative to the unemployment rate in the data and the job-finding rate 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.[14]

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

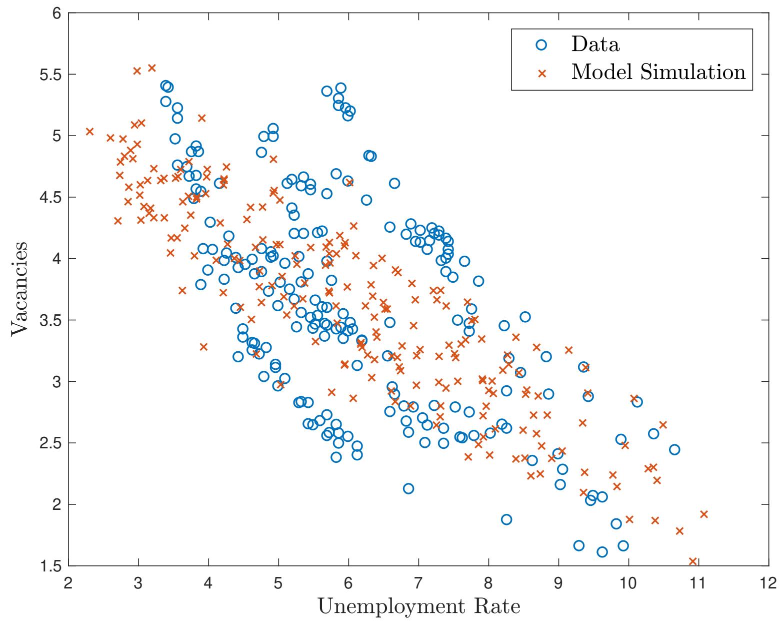

Figure 9: Beveridge curve

5.3.2 Beveridge Curve

Is our model consistent with the observed negative relationship between unemployment and vacancies in the data? To evaluate this, we compute the Beveridge curve using the most recent vacancy data (1996Q1-2016Q4) 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 -0.32. Performing the same analysis on data simulated from our model, we find a value of -0.34. Figure 9 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 plausible account of labor market fluctuations.

5.3.3 Labor Share

What does our identified shock imply for labor's share of income, and is it consistent with our model? Because we prefer not to take a strong stance on the "right" wage series, to answer the first question, we construct labor's share of income using the average response of our panel of hourly wages, together with our series for hours and real GDP. Figure 10 depicts the empirical response of labor's share of income to our identified shock from Section

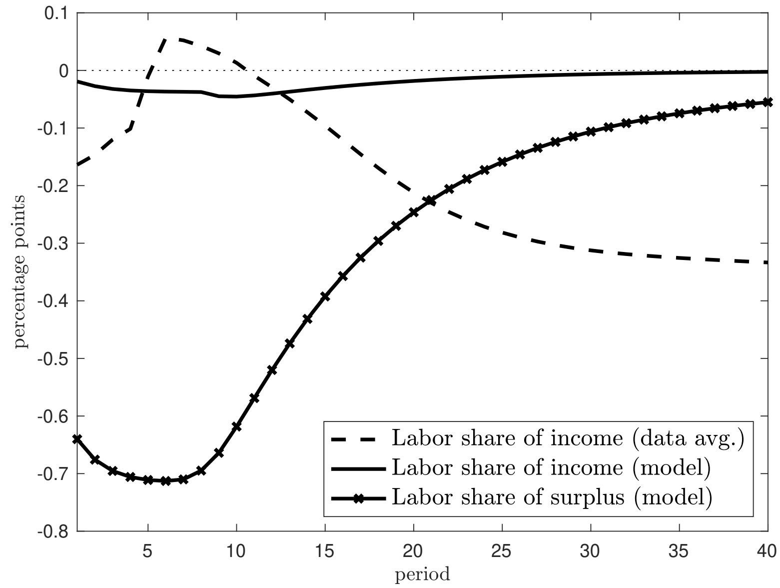

Figure 10: Labor's share of income and surplus

2. To answer the second question, we superimpose our model's implied response of labor's share of income to the news shock.

In the model, we find that labor's share falls very modestly in response to the shock, and remains negative throughout the anticipation period and after the shock is realized. In the data (using the average of our wage series), labor's share likewise falls on impact, briefly rises above its initial value when the shock is realized, before again falling to a lower level. None of these movements, however, are statistically distinguishable from a zero response. These results for the labor share of income contrast with the findings of Ríos-Rull and Santaeulàlia-Llopis (2010) for identified *surprise* technology shocks.

Despite the fact that the labor share of income is (close to) acyclical in both the model and the estimated data, we find that the model's implication for labor's share of *surplus* is much more pronounced. Labor's share of surplus is strongly counter-cyclical, falling by as much as 1.5 percentage points in response to the productivity shock. These endogenous fluctuations of labor's share of surplus are essential for the model's ability to deliver large swings in hours in response to our anticipated productivity shock.

6 Conclusion

This paper revisits a set of negative conclusions regarding the potential of productivity to be a main driver of labor market fluctuations. We show that both the data and a simple model of labor search are consistent with an important role for anticipated productivity shocks. The key requirement is a process for wages that falls modestly in response to good news about the future. Simple empirical wage measures provide tentative support for wages responding in this manner and a simple and plausible model of structural wage determination based on cash flows delivers realistic responses in our theory.

One implication of our findings is that contemporaneous correlations, for example regarding the cyclicality of wages or the correlation of TFP with other variables, can mask important dynamic relationships that suggest tighter relationships between these objects. Similarly, focusing on only a portion of the spectrum in considering covariances can lead researchers to miss relationships that exist across frequencies in the data. While these insights are not new for macroeconomists, our results suggest that business cycle researchers should continue to take these features of the data into account as they search for the origins of fluctuations.

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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 $\Delta_t \in \{Y_t, C_t, D_t, W_t, K_t, I_t\}$ 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:

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

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

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

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

$$\tilde{Y}_t = \tilde{C}_t + \tilde{I}_t + \tilde{G}_t + a_n \gamma_{x,t} V_t \tag{A.5}$$

$$\tilde{D}_t = \tilde{Y}_t - \tilde{W}_t N_t - R_t \tilde{K}_t - a_n \gamma_{x,t} V_t \tag{A.6}$$

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

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

$$R_t = \alpha \left(\frac{\tilde{K}_t}{\gamma_{x,t} N_t}\right)^{\alpha-1} \tag{A.9}$$

$$-\frac{\tilde{U}_{F,t}}{\tilde{U}_{C,t}} = (1 - p_t)\tilde{\kappa}_t + p_t \left[\tilde{W}_t + (1 - \lambda) E_t \left\{\Omega_{t,t+1} \gamma_{x,t} \left(\frac{1 - p_{t+1}}{p_{t+1}}\right) \left(-\frac{\tilde{U}_{F,t+1}}{\tilde{U}_{C,t+1}} - \tilde{\kappa}_{t+1}\right)\right\}\right] \tag{A.10}$$

$$\tilde{P}_t = \frac{\tilde{Y}_t - R_t \tilde{K}_t - a_n \gamma_{x,t} V_t}{N_t} \tag{A.11}$$

$$\tilde{W}_t = \omega_0 \tilde{P}_t^{\omega^F} \left(\tilde{W}_{t-1}/\gamma_{x,t-1}\right)^{1-\omega^F} \tag{A.12}$$

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 dyamics. We may thus proceed with any values of N and F that satisfy $\bar{un} \equiv \frac{F-N}{F} = 0.06$. We choose $\bar{N} = 0.56$ corresponding to a 56% long-run employment to population ratio (and thus a 60% long-run labor force participation rate). 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 $\bar{\mathbf{W}}_{\mathbf{t+1}} - \bar{\mathbf{U}}_{\mathbf{t+1}}$,

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

Table 5: Parameter Estimates (Nash bargaining)

Parameter	Concept	Estimate
θ	Labor supply elasticity	10.000
ϵ	Matching function elasticity	0.950
ω^{NB}	Nash Term	0.500

Replacing $\mathbf{J_t}$ with the firm's first-order condition for labor and using $\mathbf{J_{t+1}} = \frac{a_n X_{t+1}}{q_{t+1}}$,

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

Solving for W_t^{NB}, we obtain

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

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

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

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

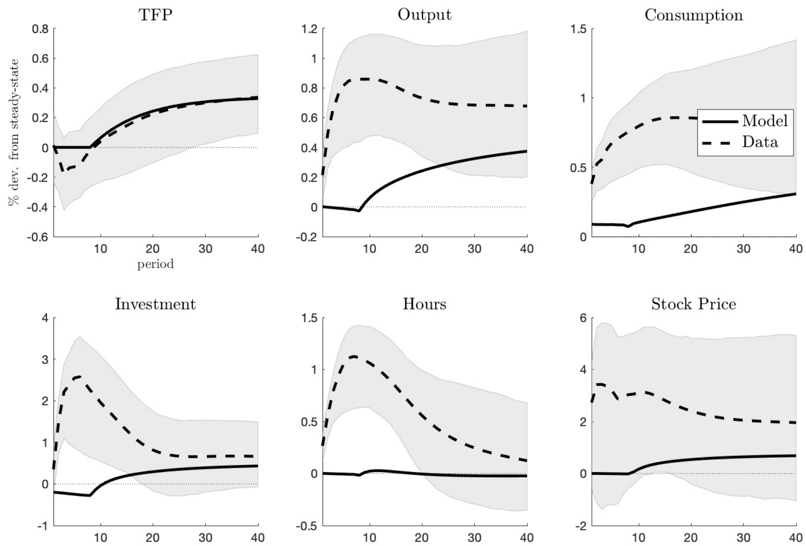

Figure 11: Estimated model with Nash bargained wage.

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 bargaining. We immediately see that all of the parameter estimates are hitting their bounds.[15] 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 11 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.

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,

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

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 11.

D Data Sources and Construction

Our main VAR specification consists of TFP, output, consumption, investment, hours, 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 expenditure 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 total private sector hours come from the BLS Labor Productivity and Costs release (Nonfarm Business Sector: Hours of All Persons) and is also divided by the population.

Lastly, our measure of real stock prices comes from Robert Shiller, and was downloaded from http://www.econ.yale.edu/ shiller/data.htm on June 1, 2019.

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 the hours series used above and the GDP deflator.

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

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 BLS's Current Establishment Survey. These series are listed in Table 6. We download each from the FRED database in nominal terms and then divide by the GDP deflator to arrive at real hourly wages.

Labor market responses are constructed adding a set 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 employment series is the BLS series of Total Non-farm Employees, again divided by the population. The unemployment series is the standard measure constructed by the BLS.

Finally, we consider two measure 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 finding rates.

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 Robustness

E.1 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, and (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 12.

As noted in the main text, our agnostic identification procedure yields impulse responses that are very similar to those implied by the news identification procedure of Kurmann and Sims (2020). Those authors identify a news shock as the shock that explains the largest portion of the forecast error of TFP at some distant horizon. Figure 13 presents the impulse responses from our estimation along with the range of point estimates generated by applying their procedure with horizons between 20 and 160 quarters. The figure shows that the

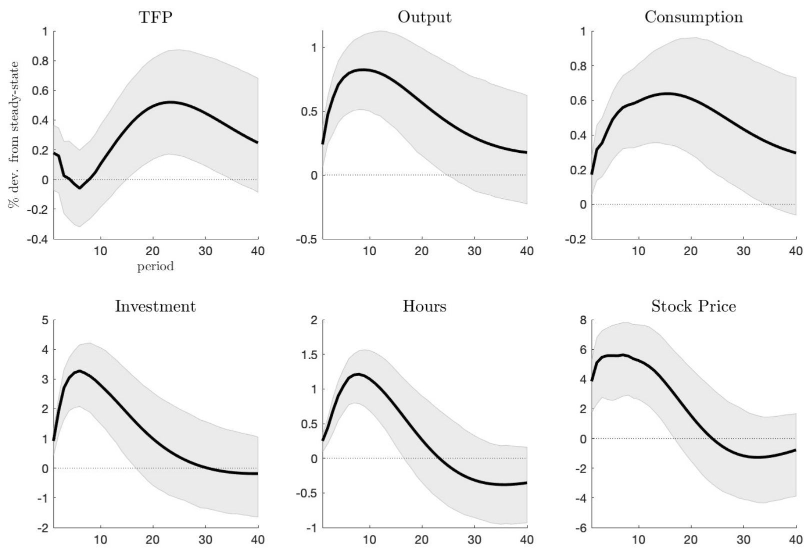

Figure 12: VAR impulse responses for the short sample starting in 1985Q1.

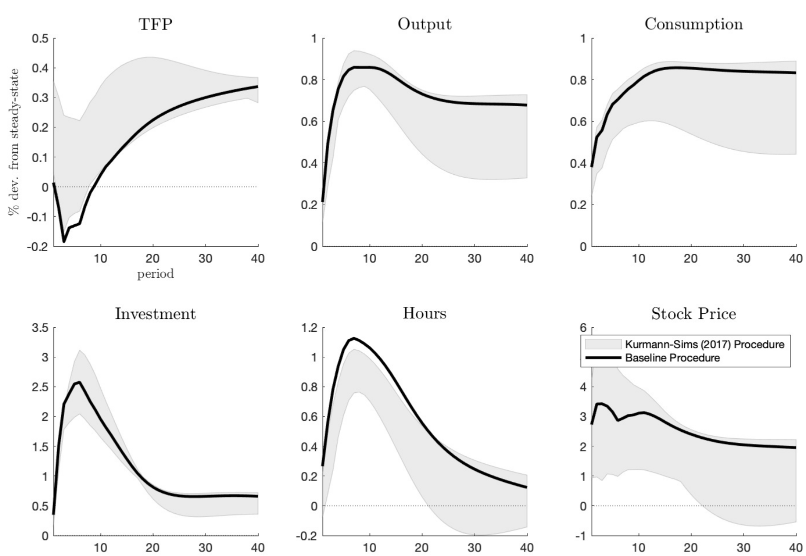

Figure 13: Comparison with the Kurmann and Sims (2020) procedure for target horizons of 20 through 160 quarters.

Table 7: Variance decompositions of VAR variables (Kurmann-Sims identification approach)

Frequency (Quarters)	**TFP**	**Y**	**C**	**I**	**N**	**S&P**
Business Cycle (6-32)	0.083	0.527	0.780	0.453	0.521	0.327
Medium run (32-100)	0.176	0.756	0.879	0.580	0.572	0.240
Long run (100-500)	0.672	0.726	0.728	0.726	0.461	0.347

impulse responses implied by this alternative procedure are quite similar to our own, except with respect to the stock price (which is marginally significant in any case.)

Another perspective on the similarity of the identified shocks comes from the implied variance decomposition. Table 7 reports the variance decomposition for their identified shock with a target horizon of $k = 40$ quarters. Comparison with Table 1 shows that the results are very close, with the identified shock explaining more than half of business cycle variation in both hours and output.

E.2 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 a version of our estimated baseline flow-wage model extended to include four additional shocks: (i) surprise, transitory productivity shocks, (ii) shocks to labor supply via stochastic fluctuations in ψ, (iii) shocks to demand via stochastic fluctuations in β, and (iv) government spending shocks. Following Fernandez-Villaverde et al. (2007), we check numerically that a VAR in [GDP,C,I,N,SP] satisfies their necessary condition for invertibility and confirm that it does.

We also show that our identification procedure does a good job in practice of identifying productivity news shocks. To do this, we calibrate the additional shocks such that each drives a substantial portion of business cycle variation in at least one variable in our data set. 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

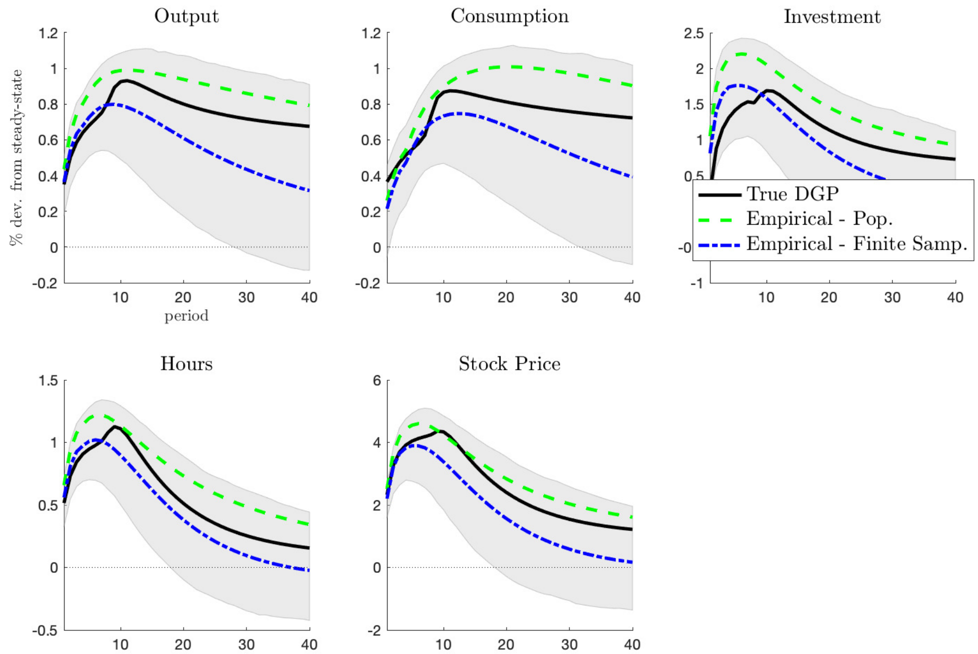

Figure 14: Suitability exercise of empirical approach using simulated data. Dashed lines show point estimates from one 20,000 period sample. Dot-dashed lines show the mean estimated response from 2,000 simulated samples of T=212 periods. Bands show the 90% confidence interval of estimated responses from among the 2,000 model simulations.

recovers the theoretical impulse responses quite well, though not surprisingly responses are slightly downward biased in the finite sample.

Table 8: Variance decompositions of theoretical variables at BC frequency

Frequency (Quarters)	**TFP**	**Y**	**C**	**I**	**N**	**S&P**
Gov. Spending	0.000	0.041	0.110	0.075	0.037	0.047
Labor Supply	0.000	0.181	0.111	0.101	0.175	0.060
Discount Factor	0.000	0.139	0.284	0.488	0.114	0.128
Surp TFP	0.688	0.117	0.146	0.046	0.053	0.023
News TFP	0.312	0.522	0.350	0.290	0.622	0.743