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Abstract

Good measures of labor market tightness are essential to predict wage inflation and to calibrate monetary policy. This paper highlights the importance of two measures of labor market tightness in determining wage growth: the quits rate and vacancies per effective searcher (V/ES)—where searchers include both employed and non-employed job seekers. Amongst a broad set of indicators of labor market tightness, we find that these two measures are independently the most strongly correlated with wage inflation both in aggregate time series data and in industry-level panel data, and also predict wage growth best out of sample. Transitory shocks to productivity have little impact on wage growth. These results are consistent with the predictions of a New Keynesian DSGE model where firms have the power to set wages and workers search on the job. Based on our findings, we develop a new composite indicator of labor market tightness that can be used by policymakers to predict wage pressures in real time.

JEL classification: E3, J6
Key words: wage Phillips curve, labor market slack, labor market tightness, on-the-job search, monopsony

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1 Introduction

> *"Nominal wages have been growing at a pace well above what would be consistent with 2 percent inflation over time. Thus, another condition we are looking for is the restoration of balance between supply and demand in the labor market."*
> **Federal Reserve Chair Jerome Powell, November 30, 2022**

The evolution of U.S. wage growth has been an object of considerable interest for policymakers in the recent high-inflation environment. However, standard measures of labor market tightness have had a mixed performance in tracking wage growth recently. For example, variation in the unemployment rate fails to explain the persistent boom in wage growth post-COVID: as panel (a) of Figure 1 shows, unemployment quickly returned to its pre-pandemic level after spiking in early 2020, while wage growth remained elevated at far above its pre-pandemic level. Developing good indicators of labor market tightness to track and predict the path of wage inflation thus remains an important task to calibrate the appropriate stance of monetary policy.

In this paper, we highlight the importance of two measures of labor market tightness in determining wage growth: the quits rate, and vacancies per effective searcher (V/ES) – where effective searchers include both employed and unemployed job seekers. These tightness measures are motivated by a tractable New Keynesian DSGE model that incorporates a frictional labor market with on-the-job search, developed in Bloesch, Lee, and Weber (2024). Those authors show in a calibrated version of their model that tightness is well-summarized either by the quits rate or vacancies per searcher, while the role of the unemployment rate for wage growth is small. We show that among a broad list of commonly used indicators of labor market tightness, the quits rate and V/ES are independently the most strongly correlated with wage growth—both in aggregate time series data and in industry-level panel regressions—and perform best in forecasting exercises, both in and out of sample, consistent with the model. A second prediction of the model is that transitory productivity shocks have ambiguous effects on nominal wage growth, and we find support for this result as well. Based on our findings, we develop a new composite indicator of labor market tightness using quits and V/ES that can be used by policymakers to predict wage pressures in real time. We find little evidence of a nonlinearity in the relationship between wage growth and our tightness measure.

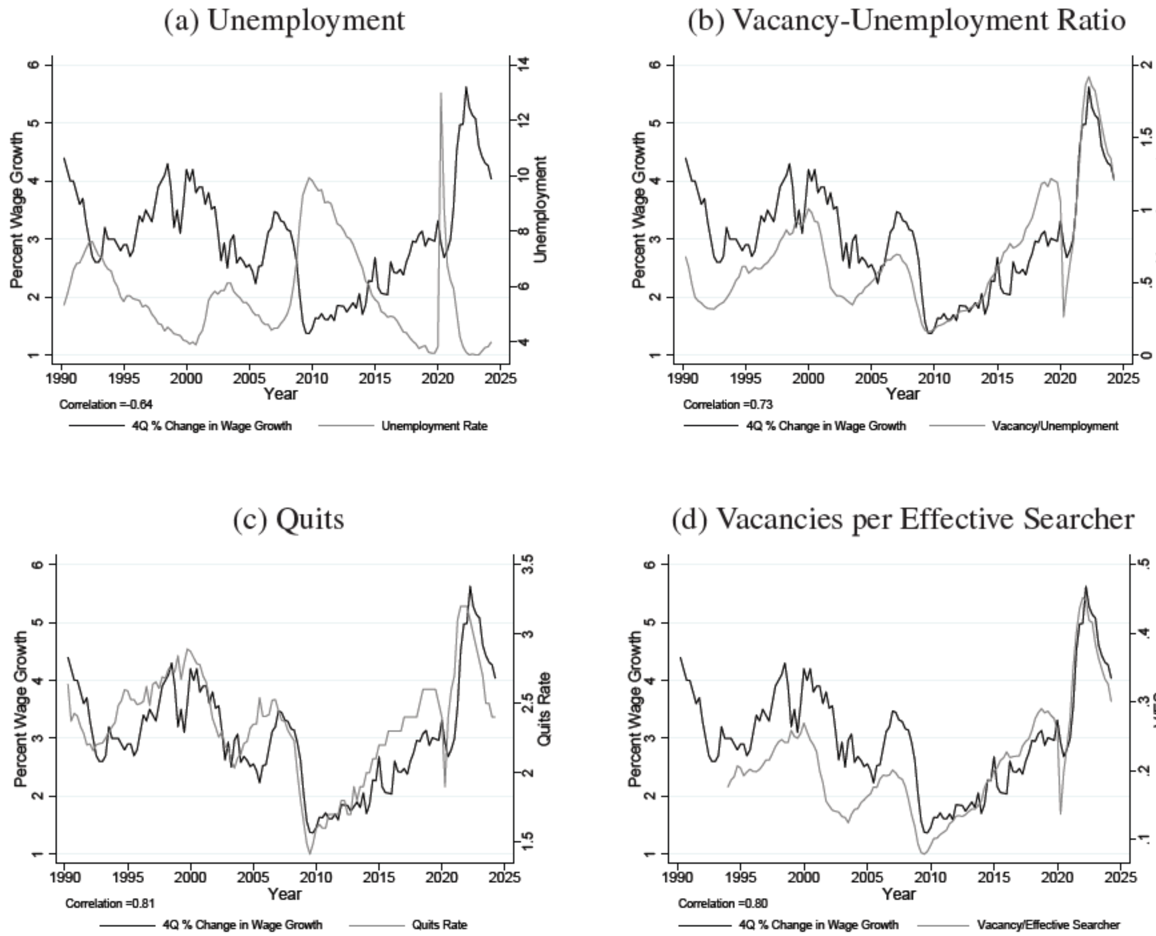
Our main analysis uses quarterly national data from the Employment Compensation Index (ECI) to measure wage growth, and relies on quits and job openings from the Job Openings and Labor Turnover Survey (JOLTS), which we extend back to 1990. We test the model's prediction that quits and vacancies per effective searcher are the best predictors of wage growth by running a "horse race" of simple linear regressions of 3-month ECI wage growth on a range of commonly used tightness measures for the period 1990:q2 to 2024:q2. These alternative tightness measures include the unemployment rate, the vacancy-to-unemployment (V/U) ratio, the vacancies-to-hires ratio, the job finding and job separation rates, the "acceptance rate" measure developed by Moscarini and Postel-Vinay (2023), the "jobs-workers gap" between available vacancies and the number of unemployed from Hatzius (2024), as well as other variables. Consistent with the theory, the quits rate and vacancies over effective searchers track wage growth the best out of all the variables tested. Quits and V/ES explain 55 percent and 52 percent of wage growth, respectively, when included in the regression individually. Together, the quits rate and V/ES explain nearly two-thirds of wage growth since 1994 and 78 percent since the onset of COVID in 2020:q2. Panels (c) and (d) of Figure 1 illustrate the tight relationship between the quits rate and vacancies over effective searchers with wage growth. Other widely used alternative indicators of labor market conditions are less strongly correlated with wage growth. For example, V/U explains only 41 percent of wage growth, and the unemployment rate only 34 percent.

We next provide support for the model's prediction that transitory productivity shocks have a negligible effect on wage growth. We obtain 3-month changes in labor productivity and in total factor productivity (TFP) from Fernald et al. (2012), and re-run the wage growth regressions with productivity shocks as the right-hand side variable. Consistent with the model, the effect on wages of transitory productivity shocks is insignificant, and the sign of the effect on wages is ambiguous.

Since the correlations we uncovered could in principle be driven by other unobserved, aggregate variables that happen to be correlated with quits and V/ES, we next conduct panel regressions of wage growth on labor market tightness indicators at the industry-level, using 11 broad sectors available from JOLTS. We run a horse race of similar wage growth regressions as before, where we include time and industry fixed effects to absorb aggregate variation and fixed heterogeneity across sectors. We find that an industry's quits rate and V/ES also have the greatest explanatory power for within-industry wage growth. Other commonly used indicators of tightness are less closely associated with wage inflation. In bivariate regressions that include both the quits rate and one other tightness variable, only V/ES has a substantial independent effect on industry wage growth once quits are accounted for.

We next investigate whether quits and V/ES can be used to predict future wage growth, and perform forecasting regressions with these variables and the alternative tightness measures. Given our finding that quits and V/ES are independently the most strongly correlated with wages, and provide the greatest fit of wage growth when used together, we construct a new composite index for labor market tightness, the *Heise-Pearce-Weber* (HPW) Index. This index is a weighted average of the quits rate and of vacancies per effective searcher, where the weights on these two variables are equal to their coefficients in a simple OLS regression of wage growth on quits and vacancies per effective searcher. We show that our new composite index, quits, and the V/ES ratio are separately the best predictors of wage growth over the next one, two, and four quarters when we

Figure 1: Wage Growth versus Labor Market Conditions



Notes: Wage growth is measured as the 12-month change in the ECI. Unemployment is from the BLS. Vacancies are obtained from JOLTS for 2001:q1-2024:q3. We use the composite Help Wanted Index constructed by Barnichon (2010) to obtain vacancies for 1990:q2-2000:q4. Quits rate for private sector workers is from JOLTS for 2001:q1-2024:q2 and from Davis et al. (2012) for 1990:q2-2000:q4. Vacancies per effective searcher are constructed as the ratio of vacancies to effective searchers, where the latter are computed as $ES = U_s + 0.48 \cdot U_l + 0.4 \cdot Z^{\text{want}} + 0.09 \cdot Z^{\text{do not want}} + 0.07N$, where U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, Z^{want} is the share of workers not in the labor force that want to work, $Z^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and N is the share of employed workers. The weights on these terms reflect the relative search intensities of these workers estimated by Abraham, Haltiwanger, and Rendell (2020) and Şahin (2020).

estimate wage regressions over the entire sample period.

We then perform out-of-sample forecasting regressions and predict 3-month wage growth in the next quarter using only available information up to the current quarter, starting with the prediction for 2004Q1. We evaluate the size of the prediction error by computing root mean squared errors (RMSE) over 40 quarter rolling windows. We find that over the last 20 years, the quits rate and the HPW Index were the best out-of-sample predictors of wage growth, and the only ones to consistently outperform a simple AR(1) model of wage inflation. Our new index could therefore be a useful instrument for policymakers to predict wage inflation in real time. We also find that the out-of-sample forecasting performance of vacancy-based tightness measures V/U and V/ES has steadily deteriorated since 2015, possibly due to issues in the measurement of vacancies highlighted by Mongey and Horwich (2023), who find that the once-stable relationship between job vacancies and other labor market indicators has persistently shifted since 2010.

The out-of-sample forecasts also reveal that the forecasting performance of unemployment and several other standard measures of labor market tightness (though not the quits rate or the HPW Index) deteriorated sharply in the post-COVID period. Given that wage inflation surged to unusually high levels at this time, this failure could arise from fitting a linear model for, e.g., the unemployment-wage relationship instead of a more appropriate nonlinear model. However, we find little evidence that this is the case: threshold regressions of wage inflation on unemployment, V/ES, and quits provide little evidence of meaningful nonlinearities in our post-1990 sample. In short, there appears to be nothing unusual about the wage/tightness relationship during the period of extreme tightness in the aftermath of COVID.

Related Literature. Since its original empirical formulation by Phillips (1958), many academic authors and policymakers have estimated reduced-form relationships between wage growth and labor market tightness (e.g., Hooper, Mishkin, and Sufi, 2020; Blanchard and Bernanke, 2023). Our work is closely related to Galí (2011) and Bloesch, Lee, and Weber (2024) who each provide a novel microfounded wage Phillips curve based on OLS regressions in U.S. data. Galí (2011) provides foundations for a wage Phillips curve with unemployment as the forcing variable, while Bloesch, Lee, and Weber (2024) do the same but for a wage Phillips curve with quits and unemployment, demonstrating that unemployment plays a minimal role in determining wage growth both in their model and in aggregate U.S. data. In this paper, we compare the two key measures from their model—quits and vacancies per effective searcher, which are predicted to be tightly related—against a broad range of other commonly used indicators, both in the aggregate and in cross-sectional industry regressions, as well as studying their out-of-sample forecasting performance. This approach is most similar to Barnichon and Shapiro (2024), who study OLS estimates of the *price* Phillips curve in U.S. data and compare the out-of-sample forecasting performance of various measures of labor market tightness for *price* inflation using local projections (Jordà, 2005). We perform similar exercises for U.S. *wage* inflation.

Relative to recent work specifically demonstrating the strong empirical relationship between quits, or job-to-job transitions, and wage growth (e.g., Faberman and Justiniano, 2015; Moscarini and Postel-Vinay, 2017; Karahan et al., 2017; Barnichon and Shapiro, 2022; Bloesch et al., 2024), we investigate the relationship of wage growth with a broader range of labor market tightness indicators in a "horse race" with quits and vacancies per effective searcher, as well as Total Factor

Productivity (TFP) shocks. We also perform out-of-sample predictions and investigate the presence of nonlinearities in the *wage* Phillips curve.

Accordingly, our work is related to a recent revival of interest in nonlinear estimates of the Phillips curve: recent work shows that the U.S. *price* Phillips curve appears nonlinear both in terms of unemployment (Cerrato and Gitti, 2022) and in terms of the vacancy-to-unemployment ratio (Crust et al., 2023; Gitti, 2024; Benigno and Eggertsson, 2024). We focus on nonlinear estimates of the *wage* Phillips curve. Indeed, the idea of a wage Phillips curve which is nonlinear in *unemployment* goes back to Phillips (1958) and has been investigated empirically for the U.S. in both the aggregate and subnational levels (Donayre and Panovska, 2016; Kumar and Orrenius, 2016; Hooper, Mishkin, and Sufi, 2020); and these results have inspired work that provides microfoundations for a nonlinear wage Phillips curve from downward nominal wage rigidity (Daly and Hobijn, 2014; Schmitt-Grohé and Uribe, 2023). We depart from this literature by studying measures of labor market tightness that account for the presence of on-the-job search (i.e., quits and vacancies per effective searcher). We show that quits or a labor market index that incorporates quits fit the wage data well, have good forecasting properties, and do not exhibit a nonlinear relationship with wages, including through the COVID period.

Finally, we acknowledge that our choice of underlying model is driven largely by tractability, as other New Keynesian DSGE models with on-the-job search also predict that job-to-job transitions are correlated with wage growth (e.g., Faccini and Melosi, 2023; Moscarini and Postel-Vinay, 2023). However, the microfoundations in Bloesch, Lee, and Weber (2024) admit a simple representation of the wage Phillips curve similar to what has been used in applied work for estimating the wage Phillips curve in terms of unemployment (e.g., Phillips, 1958; Galí, 2011) or other measures of labor market tightness (e.g., Barnichon and Shapiro, 2022). It also admits a two-period, AD-AS representation that clarifies the minimal role of *transitory* productivity shocks on nominal wages, which we test in the data as well.

Roadmap. The rest of the paper proceeds as follows. In Section 2 we briefly describe the theoretical model used to inform our regression estimates and present the key equations that we take to the data. Section 3 analyzes the correlation of wage growth with various labor market variables and productivity. We then develop our composite index of labor market tightness in Section 4 and perform forecasting regressions and out-of-sample predictions. Section 5 examines nonlinearities in the wage Phillips curve. Finally, Section 6 concludes.

2 Conceptual Framework and Measuring Tightness

In this section, we discuss the microfoundations of the empirical analysis in our paper. Specifically, to develop intuition behind the wage Phillips curve specification that we take to the data, Section 2.1 presents a slightly simplified version of Bloesch, Lee, and Weber (2024), which highlights the main empirical components of our framework. Section 2.2 briefly reviews other theoretical frameworks for measuring labor market tightness and connects them to objects in the data we construct for our empirical exercises.

2.1 A Model with On-the-Job Search and Firms' Wage Setting

Bloesch, Lee, and Weber (2024) develop a tractable DSGE model with wage setting under nominal rigidities and on-the-job search, which allows them to study the effects of quits, vacancies, and unemployment on wage inflation in a unified model.[1] The wage Phillips curve implied by this model informs the specification of our simple regressions of wage growth on measures of labor market tightness below.

In the model, workers search in a frictional labor market when unemployed and on the job when employed. Each firm j uses wages W_{jt} and vacancies V_{jt} as two alternative tools to attract and retain workers from unemployment and from other firms. A firm j's employment N_{jt} in period t decreases due to worker separations and increases due to recruiting according to

$$N_{jt} = (1 - S_t(W_{jt}))N_{j,t-1} + V_{jt}R_t(W_{jt}), \tag{1}$$

where $S_t(W_{jt})$ is the rate at which workers separate from the firm, which is decreasing in the firm's wage posting, and $R_t(W_{jt})$ is the firm's recruiting rate, which increases in the firm's wages. The law of motion shows that setting higher wages allows a firm to increase the chance that a given job offer is accepted by a worker and raises the probability of retaining the worker in the face of other firm's job offers. Alternatively, posting more vacancies increases the firm's likelihood of meeting a worker and of forming a match. Separation and recruiting rates are time-varying because of movements in aggregate labor market tightness: a tight labor market makes it harder to find workers and more likely that workers are poached by other firms.

A firm maximizes the present discounted value of profits by choosing prices P_{jt}, wages W_{jt},

[1] While the model produces a price Phillips curve as well, we focus on the model's predictions for wages.

and vacancies V_{jt} to solve

$$\max_{\{P_{jt}\},\{W_{jt}\},\{V_{jt}\}} \sum_{t=0}^{\infty} \left(\frac{1}{1+\rho}\right)^t \left(P_{jt}Y_{jt} - W_{jt}N_{jt} - cV_{jt}W_t - \frac{\psi^w}{2}\left(\frac{W_{jt}}{W_{j,t-1}} - 1\right)^2 W_{jt}N_{jt}\right), \tag{2}$$

subject to the law of motion (1). Here, Y_{jt} is the output quantity and W_t is the aggregate wage. Moreover, ρ is the discount rate, c is a vacancy adjustment cost, and ψ^w is a wage adjustment cost parameter.

The model generates a mass of searchers that is greater than in a standard labor market model such as Mortensen and Pissarides (1999) since a share of employed workers also search. Instead of $\frac{V_t}{U_t}$, labor market tightness is $\theta_t \equiv \frac{V_t}{\mathcal{S}_t}$: vacancies V_t divided by the mass of active searchers, $\mathcal{S}_t = \lambda_{EE}N_{t-1} + U_{t-1}$, where N_{t-1} is the mass of employed workers entering period t, U_{t-1} is the mass of unemployed, and λ_{EE} is the employed workers' search intensity. Since there are many more employed workers than unemployed in the U.S. economy, most job searchers are employed even though $\lambda_{EE} < 1$. This definition of searchers is similar to the generalized tightness measure proposed by Abraham, Haltiwanger, and Rendell (2020) and Şahin (2020).

Using the first-order conditions of the firm's problem (2) for vacancies and wages, Bloesch, Lee, and Weber (2024) show that up to a first order we can write the wage Phillips curve as:[2]

$$\check{\Pi}_t^w = \beta_\theta \check{\theta}_t + \beta_U \check{U}_{t-1} + \frac{1}{1+\rho}\check{\Pi}_{t+1}^w \tag{3}$$

where the "check" ($\check{x}$) variables denote log deviations from steady state. This is very similar to the wage Phillips curve derived in Galí (2011), equation (13), but with an additional labor market tightness term θ_t in addition to unemployment. This additional term results from the different microfoundations: namely, the assumption that firms set wages and workers search on the job in a frictional labor market, as opposed to assuming workers or their unions unilaterally set wages and supply labor to meet demand following Erceg, Henderson, and Levin (2000) as assumed by Galí (2011). The wage Phillips curve includes θ_t, rather than V/U, because of the presence of on-the-job searchers: intuitively, since unemployed workers are not the only job searchers, labor market tightness is not V/U but $\theta \equiv V/\mathcal{S}$. In the model, when θ_t is high, workers are harder to both recruit and retain, putting pressure on firms to raise wages (i.e., $\beta_\theta > 0$).

The appearance of unemployment U_{t-1} in equation (3) reflects the fact that the *composition* of searchers matters for wage growth. Because unemployed workers almost always accept job offers, their job-taking decision is not very sensitive to the offered wage, in contrast to the decision by

[2]In one specification of the model, Bloesch, Lee, and Weber (2024) provide microfoundations for an additional term in the wage Phillips curve reflecting the real wage in the previous period. We omit this term as those authors argue its coefficient is small both in the calibrated model and in the data.

employed workers. Thus, when U_{t-1} is high and relatively more searchers are unemployed, optimizing firms prefer to acquire workers by posting vacancies, rather than raising wages. However, Bloesch, Lee, and Weber (2024) find that $\beta_U \approx 0$ both in the calibrated model and in reduced-form OLS regressions on U.S. data: even if unemployed workers' job-taking decision is much less wage-sensitive than employed workers' decision, changes in unemployment U_{t-1} do not change the composition of searchers much.

An additional difference between the wage Phillips curve (3) and the one in Galí (2011) is that price inflation or price inflation expectations do not appear. These matter for wage inflation in general equilibrium, but only through the tightness term: if inflation expectations rise (e.g., due to a monetary policy shock), firms pull workers out of unemployment to meet demand by posting more vacancies and raising wages, increasing aggregate labor market tightness and wage inflation. Similarly, monetary policy (i.e., demand) shocks and TFP shocks do not appear directly in the wage Phillips curve because they only raise wages through their general equilibrium effects on labor market tightness in the model. If these are the only shocks in the model, then the right-hand side of equation (3) describes a "sufficient statistic" for wage inflation. This discussion also illustrates that there are fewer identification issues for the slope of the model's wage Phillips curve than for the model's price Phillips curve: in the price Phillips curve, the endogenous response of monetary policy to TFP shocks is an omitted variable and biases the slope of the price Phillips curve towards zero. In the wage Phillips curve derived above, TFP and monetary policy shocks only affect the tightness variable itself and so the slope can be consistently estimated. For further discussion on why we should expect reduced-form wage Phillips curves to have fewer issues with identification and to be more readily observable in the data, see Section IV.D of McLeay and Tenreyro (2020).

Using the tight relationship between vacancies and quits Q_t, which are the endogenous component of separations, Bloesch, Lee, and Weber (2024) show that alternatively wage inflation can be written as a function of quits and unemployment:

$$\check{\Pi}_t^w = \beta_Q \check{Q}_t + \beta_U \check{U}_{t-1} + \frac{1}{1+\rho}\check{\Pi}_{t+1}^w. \tag{4}$$

Because workers receive more job offers and thus quit more frequently when labor market tightness is high, the model predicts that either quits Q_t or vacancies over searchers θ_t belongs in the wage Phillips curve—along with unemployment. As before, Bloesch, Lee, and Weber (2024) show that the role of the unemployment term in (4) is relatively small in this formulation of the wage Phillips curve as well.

Overall, a key takeaway from the model is that, given unemployment, either quits or vacancies over searchers θ_t are both *complete* measures of labor market slack, as no other variables appear in the wage Phillips curves (3) or (4) above. In general, we might not expect this prediction to hold perfectly in the data, since we may not be able to measure vacancies, searchers, and quits perfectly. However, the model broadly predicts that quits should perform much better than unemployment in predicting wage growth, and that V/U should perform worse than a measure of V over all job searchers (i.e. $V/\mathcal{S}$). Moreover, given recent work highlighting issues in the consistent measurement of vacancies over time (Mongey and Horwich, 2023), we might also expect quits to perform better than measures of $V/\mathcal{S}$ in predicting wage growth.

A second implication of the model is that the effect of productivity shocks on wage growth is ambiguous and depends on its effects on labor market tightness. Bloesch et al. (2024) show that positive, *transitory* TFP shocks can either move wage inflation and tightness up or down, depending on how responsive monetary policy is to inflation. Intuitively, if the central bank commits to keeping the current and expected path of real interest rates fixed, then a positive, transitory shock to TFP today reduces the amount of labor needed to meet fixed household demand. Optimizing firms respond by reducing both vacancies (tightness) and wages, leading to lower employment. Because marginal costs fall, prices and inflation also fall in equilibrium. In contrast, if the central bank *reduces* real interest rates in response to the disinflation caused by the shock, following a standard Taylor rule, aggregate consumption will rise as the real interest rate falls. If it rises enough (i.e. if the real rate falls sufficiently) then firms will have to hire more workers to meet demand, even though workers have become more productive. Since firms increase employment by posting more vacancies and raising wages, this induces a positive correlation between TFP shocks and wage growth.[3] We test this second implication of the model below as well.

2.2 Alternative Measures of Tightness

While the theory above connects $V/\mathcal{S}$ and quits to wage growth, other measures of tightness have previously been linked to wage inflation. In this section, we briefly describe these alternative measures. We will use them in a "horse race" in Section 3 to show that quits and $V/\mathcal{S}$ perform best in predicting wage inflation, consistent with the theory outlined above. Appendix A contains further documentation on each measure of tightness we consider in the paper.

A standard measure of tightness in the labor market is the unemployment rate, since at least Phillips (1958). In Galí (2011), the unemployment gap is the forcing variable in the wage Phillips curve. When unemployment is high relative to its natural rate, wages are too high to clear the labor market, leading to relatively low wage inflation going forward. Barnichon and Shapiro (2022) also

[3]The amount of market power firms have also determines the outcome: if firms do not pass on productivity gains to their customers in the form of lower prices, then inflation does not fall, the central bank does not lower interest rates, and demand will remain fixed: the outcome is lower employment and lower wages. See the supplementary online appendix to Bloesch et al. (2024) available on those authors' websites here for more details.

include the unemployment rate as a measure of labor market slack in their analysis of price and wage inflation.

An alternative measure of labor market slack is the vacancy-to-unemployment (V/U) ratio. This measure is tightly linked to models that build on the Diamond-Mortensen-Pissarides (DMP) framework (e.g., Mortensen and Pissarides, 1999).[4] When vacancies are high relative to unemployment, firms find it easier to recruit, which lowers wages. Ball et al. (2022) and Benigno and Eggertsson (2024) use the V/U ratio as an index of labor market slack to derive insights on price inflation. Bloesch et al. (2024) show that this is the correct measure of labor market tightness on the right-hand-side of the wage Phillips curve in the limiting case of their model without on-the-job search.

Relatedly, some authors have considered the vacancies-to-hires ratio as a measure of labor market tightness (Hall and Schulhofer-Wohl, 2018). When this ratio is high, it means there are many vacancies and few hires, so open positions take a long time to be filled (i.e., the duration of a vacancy is high). Intuitively, we might expect this measure to be correlated with wage growth: if firms are having a hard time attracting job seekers—which can include on-the-job searchers—to fill open positions, it may lead them to raise wages.

Another indicator of the relative bargaining power of firms and workers is the job finding rate (Moscarini and Postel-Vinay, 2017). A high job finding rate indicates that workers have a strong bargaining position, which means that they can obtain higher wages. On the flipside, a higher job-separation rate suggests that labor demand is lower than supply, reducing workers' bargaining power and wage pressures.

In on-the-job search models such as Burdett and Mortensen (1998), real wage growth is tightly linked to job-to-job transitions. Workers move jobs when they receive job offers that pay them more than their current position. Wage growth is therefore affected by the behavior of employed workers, which constitute a much larger pool of workers than the unemployed. This measure is closely related to the quits rate, which we already discussed above. Karahan et al. (2017) show that job-to-job transitions outperform the unemployment rate in explaining wage growth, and Moscarini and Postel-Vinay (2016) show that the rate of these job transitions is nearly a sufficient statistic for the average wage under certain restrictions.

A related measure has recently been proposed by Moscarini and Postel-Vinay (2023). They argue that the ratio of the job finding probability job-to-job and the job finding probability from unemployment is negatively related to inflation (they refer to their measure as the "acceptance rate"). Given the job finding probability from unemployment, which they argue measures labor demand, a higher job finding probability job-to-job indicates that there exists slack in the labor

[4] Since these models do not contain prices, nominal and real wages have a one-to-one relationship in the models. These models are also usually steady state models and therefore speak more to the *level* of wages than to wage inflation.

market, as workers move around relatively frequently. In that case wage pressures should be low. Moscarini and Postel-Vinay (2023) show that their measure performs well in tracking wage inflation in the post-Covid period.

Another tightness measure is the jobs-workers gap, defined as the difference between the mass of vacancies and the number of unemployed. Hatzius (2024) finds that this variable is a better measure of labor market slack than the unemployment rate. Wage growth should be high when vacancies are plentiful relative to the number of unemployed.

Finally, we consider three additional measures of labor market tightness. First, we include the hires rate, i.e., hires divided by employment. Second, we include the Conference Board's Labor Market Differential, which measures the difference between the share of respondents that report jobs being plentiful relative to hard to get.[5] A high differential suggests that it is easy for workers to find jobs, strengthening their bargaining position and pushing up wage growth. Third, we include the National Federation of Independent Businesses' (NFIB) share of businesses with few or no qualified applicants for job openings.[6] A high share indicates that workers are hard to get, generating wage pressures. This measure has been used by, e.g., Kudlyak and Miskanic (2024) in their analysis of firms' perceptions of labor market tightness.

3 Empirical Determinants of Wage Growth

We now analyze the correlation of wage growth with these measures of labor market tightness. The model's wage Phillips curves (3) and (4) imply a strong relationship between wage inflation, vacancies over searchers, and quits. We are particularly interested in comparing the performance of the model's measures of tightness to the alternative measures of labor market tightness introduced in Section 2.2. We also evaluate the model's prediction that productivity shocks have an ambiguous effect on wage inflation.

3.1 A "Horse Race" of Tightness Measures

We run OLS regressions of wage inflation on tightness measures individually and jointly, following empirical work since at least Phillips (1958). To facilitate the comparison of the different scales of the variables, we normalize all right-hand side variables to have mean zero and standard deviation of one. We do not normalize the left-hand side wage growth variable. Hence, regression coefficients indicate the the percentage change in wage growth associated with a one standard deviation

[5] See https://www.conference-board.org/topics/consumer-confidence

[6] See https://www.nfib.com/news-article/monthly-report/jobs-report

increase in each independent variable. Our regressions take the form

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{5}$$

where Π_t^w is wage inflation between quarter $t-1$ and quarter t and X_t is the normalized tightness measure in quarter t.

Characterizing the variables in deviations from their mean is consistent with the Phillips curve equations, which express the relationship of the variables in deviations from steady state. We assume that the steady state is equal to a variable's unconditional mean in our sample period. We provide additional robustness checks below.

We implement the regression using quarterly U.S. data for the period 1990:q2-2024:q2, where the start of the sample is dictated by the availability of data on quits. Throughout our analysis, we use the Employment Cost Index (ECI) for wages and salaries of private industry workers as our measure of wages, following, e.g., Blanchard and Bernanke (2023).[7] We compute the 3-month log change in the ECI as our measure of wage growth. We obtain the quits rate for private sector workers from JOLTS from 2001:q1 onwards, and extend it backward to 1990:q2 using the data from Davis, Faberman, and Haltiwanger (2012). The vacancy data for the tightness measures are also from JOLTS from 2001:q1, extended backwards using the composite Help Wanted Index constructed by Barnichon (2010) for 1990:q2-2000:q4. For both vacancies and quits we take a simple average of the JOLTS measure and the other measure in quarters in which both are available. See Appendix E for further details.

We construct the vacancies per searcher measure, $V/\mathcal{S}$, as vacancies per *effective* searcher, V/ES, which takes into account the search intensity of different types of workers. The simple model introduced above does not have a nonemployment margin and may therefore miss that workers that are out of the labor force also search for jobs. Following Abraham, Haltiwanger, and Rendell (2020) and Şahin (2020), we construct the ratio of V/ES to incorporate job search from nonemployment and distinguish between short- and long-term unemployment. Effective searchers are defined as $ES = U_s + 0.48 \cdot U_l + 0.4 \cdot Z^{\text{want}} + 0.09 \cdot Z^{\text{do not want}} + 0.07N$, where U_s is the share of individuals that are unemployed less than 27 weeks in the population 16 years and older, U_l is the share of individuals unemployed for at least 27 weeks, Z^{want} is the share of workers not in the labor force that want to work, $Z^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and N is the share of employed workers. The weights on these terms reflect the relative search intensities of these workers estimated by Abraham, Haltiwanger, and Rendell (2020), translated to more readily available data by Şahin (2020).[8] We obtain measures of

[7] As those authors note, for our purposes ECI is preferable to other employer-based survey measures like Average Hourly Earnings because it corrects for changes in earnings due to changes in the composition of employment.

[8] Şahin (2020) shows that this measure closely tracks the more detailed measure developed by Abraham, Halti-

employment, unemployment, and workers not in the labor force from the CPS, using the number of marginally attached workers for Z^{want} and defining the remaining workers 16 years and older that are not in the labor force as those that do not want a job, $Z^{\text{do not want}}$. We consider V/ES the empirically appropriate measure of labor market tightness. Details are in Appendix A.

We construct the alternative measures of labor market tightness described above. We measure unemployment using both the official unemployment rate (U-3) and continuing claims for unemployment insurance, and construct V/U using U-3 and our measure of vacancies described above. We retrieve the acceptance rate measure from Fujita, Moscarini, and Postel-Vinay (2024), and compute the jobs-workers gap as (Vacancies - Unemployment), normalized by the size of the labor force. The hires rate is obtained from JOLTS and extended backwards to 1990:q2 using the data by Davis, Faberman, and Haltiwanger (2012) in the same way as the quits rate. We compute the hires / vacancies ratio using our extended series from 1990:q2. The NFIB Index of the Difficulty Hiring and the Conference Board jobs availability measure are retrieved from Haver Analytics. To compute the job finding rate and the separation rate, we use CPS worker flows and apply the methodology by Shimer (2012). We provide further details in Appendix A.

We include the quits rate but do not separately run regressions using the job-to-job transition rate due to data availability. A measure of job-to-job flows is constructed by the Census Bureau based on LEHD data, but it only becomes available with a delay of more than one year, rendering it less useful for policymakers. Moreover, it is only available for the relatively recent period, starting in 2000, rather than for our full sample period. Similarly, one could construct job-to-job transitions using the CPS micro data, but this measure is quite noisy given the limited sample size. Since a large share of quits are transitions to other employers, we focus on the quits rate in our analysis.

Table 1 reports results of estimating equation (5) separately with each of the various tightness measures. Given the persistence of the right-hand side variables, we do not report standard errors and instead focus on reporting the estimated standardized coefficient and the model fit, as measured by the R-squared; Appendix B Table A.1 reports standard regression tables underlying these results, with Newey-West standard errors. The tightness measures are ranked by their ability to fit U.S. wage data since 1990. Consistent with the model, the unemployment rate is negatively correlated with wage growth while V/ES and the quits rate are positively correlated with wage growth. Also consistent with the model, quits and V/ES top the list in terms of their ability to track contemporaneous wage growth, with unemployment being relatively less important. A one standard deviation decrease in unemployment (by 1.8 percentage points) is associated with a 3-month increase in wage growth of 0.16 percentage points. Instead, a one standard deviation increase in V/ES (by 0.08) or quits (by 0.39) is associated with an increase in wage growth of 0.20 percentage points. The R-squared in both the regressions involving V/ES and quits is substantially higher

wanger, and Rendell (2020) but can be estimated publicly available data.

Table 1: Nominal Wage Growth and the Labor Market Tightness Measures Ranked by Fit

Measure X_t	**Coefficient on X_t**	**Fit**
Quits Rate	0.20	0.55
V/ES	0.20	0.52
Jobs-Workers Gap	0.18	0.44
V/U	0.17	0.41
NFIB Difficulty Hiring	0.17	0.41
Conference Board Jobs Availability	0.17	0.40
Unemployment	-0.16	0.34
Job Finding Rate	0.15	0.33
Acceptance Rate	-0.16	0.30
Hires Rate	0.12	0.21
Continuing Claims	-0.12	0.19
Vacancy/Hire	0.10	0.15
Separation Rate	0.00	0.00

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, while "Fit" reports the R-squared value from the simple univariate time-series regression (5): $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. All measures of tightness are ordered by their fit. Estimates use data from 1990:Q2–2024:Q2, when quits data are available, or shorter horizons in the few cases where less data are available. Definitions of all measures can be found in Appendix A; underlying OLS regressions can be found in Appendix B Table A.1.

than the R-squared for unemployment, explaining more than half of the variation in wage growth.

While some of the alternative tightness measures do not have a direct correspondence in the model developed above, empirically they may provide further information on the strength of the labor market and thus may be relevant for wage growth. Alternatively, they may simply reflect a correlation with the quits rate, the variable most highly correlated with wage growth above. To investigate this possibility, we next run regressions of the form:

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t \tag{6}$$

where X_t is the standardized tightness measure in Table 1 above, and Q_t is the quits rate. Table 2 presents a set of coefficients on bivariate regressions that include quits alongside the other variables X_t. We present both coefficients and the R-squared (fit). Appendix B Table A.2 contains the associated standard regression tables with Newey-West standard errors.

We find that quits and V/ES are the strongest together, and quits consistently has the highest coefficient value associated with it. When considering unemployment, note that this is the exact regression suggested by the model in equation (4), where the coefficient on unemployment is expected to be close to zero. Estimating the bivariate regressions yields results consistent with this prediction from the model: once the quits rate is included in the regression, changes in the unemployment rate are no longer associated with changes in wage growth, and the coefficient on unemployment drops to effectively zero. Indeed, we obtain this same result for all other measures

Table 2: Bivariate Regressions with Nominal Wage Growth: Quits and Others

Measure X_t	**Coefficient on X_t**	**Quits Coefficient**	**Fit**
V/ES	0.08	0.14	0.60
Acceptance Rate	0.02	0.22	0.60
NFIB Difficulty Hiring	0.01	0.19	0.57
V/U	0.04	0.17	0.56
Vacancy/Hire	0.02	0.19	0.56
Separation Rate	0.03	0.20	0.56
Jobs-Workers Gap	0.02	0.18	0.55
Conference Board Jobs Availability	-0.01	0.21	0.55
Job Finding Rate	0.01	0.20	0.55
Unemployment	0.00	0.20	0.55
Hires Rate	-0.00	0.20	0.55
Continuing Claims	0.00	0.20	0.55

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, or β_1 from regression (6): $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$. "Quits Coefficient" reports the coefficient on quits, β_2 and "Fit" reports the R-squared value. All measures of tightness remain ordered by their fit. Estimates use data from 1990:Q2–2024:Q2, or shorter horizons when less data are available. This table shows that conditional on quits, none of the other indicators matter much for wage growth; the coefficients on the alternatives shrink to nearly zero while the coefficient on quits remains large and unchanged. Definitions of all measures can be found in Appendix A; underlying OLS regressions can be found in Appendix B Table A.2.

of tightness we consider. Once we incorporate quits, the other variables contain little to no additional information for wage growth. Their coefficients drop to nearly zero, while the coefficient on quits remains relatively unchanged from its value in Table 1. This result is consistent with the models' prediction that quits, or equivalently V/ES, are nearly complete summaries of labor market tightness. The results are also consistent with quits being a slightly more accurate measure of labor market tightness than V/ES, possibly due to issues in the measurement of vacancies highlighted by Mongey and Horwich (2023)

We examine the robustness of our results by re-running all regressions using 12-month changes in ECI as dependent variable instead of 3-month changes to analyze whether our results hold over longer horizons. Specifically, we now run

$$\Pi_t^{w,12} = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{7}$$

where $\Pi_t^{w,12}$ is now the 12-month change in the ECI between quarter $t-4$ and quarter t, and X_t are the same tightness measures as before. Table 3 shows the results from these regressions; see Appendix B, Table A.3 for a standard regression table with Newey-West standard errors. As before, the quits rate and V/ES have the greatest standardized coefficients and fit, explaining about two-thirds of the variation in wage growth.

Table 3: 12-Month Wage Growth and Tightness Measures

Measure X_t	**Coefficient on X_t**	**Fit**
Quits Rate	0.18	0.66
V/ES	0.18	0.64
Jobs-Workers Gap	0.16	0.52
V/U	0.16	0.52
Job Finding Rate	0.16	0.50
Acceptance Rate	-0.16	0.49
NFIB Difficulty Hiring	0.16	0.49
Conference Board Jobs Availability	0.15	0.49
Unemployment	-0.14	0.41
Hires Rate	0.12	0.29
Continuing Claims	-0.10	0.20
Vacancy/Hire	0.09	0.17
Separation Rate	0.02	0.01

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, while "Fit" reports the R-squared value from the simple univariate time-series regression (8): $\Pi_t^{w,12} = \beta_0 + \beta_1 X_t + \epsilon_t$. All measures of tightness are ordered by their fit. Estimates use data from 1990:Q2–2024:Q2, when quits data are available, or shorter horizons in the few cases where less data are available. 12-month wage growth is defined as the change in the ECI for wages and salaries of private industry workers between quarter $t-4$ and t. Definitions of all tightness measures can be found in Appendix A; underlying OLS regressions can be found in Appendix B Table A.3.

3.2 Productivity

We next examine the model prediction that productivity shocks have ambiguous effects on wage growth. We perform similar national regressions with productivity as in the previous tables, using commonly used measures of total factor productivity (TFP) and labor productivity shocks. Specifically, we obtain 3-month changes in productivity from Fernald et al. (2012), and use three different definitions of productivity as our independent variables. We run the following,

$$\Pi_t^w = \beta_0 + \beta_1 Z_t + \epsilon_t, \tag{8}$$

where Π_t^w is contemporary wage growth and Z_t is a measure of productivity. We focus on three possible measures in Table 4. As before, regressions are run for the period 1990:q2-2024:q2.

Since the productivity shocks are more plausibly exogenous and less persistent than the tightness measures above, we show a standard regression table here and use causal language in discussing the results. We find that in general, transitory productivity shocks do not show a strong negative or positive effect on wage inflation, which is consistent with the predictions of the model. This is the case whether productivity is measured as labor productivity, TFP, or utilization-adjusted TFP. While the coefficient is negative in all three cases, it is statistically indistinguishable from zero. Compared to other measures of the labor market, productivity is much weaker at predicting

Table 4: ECI and Productivity

Indep. Var	(1) Labor Productivity 3-month change	(2) TFP 3-month change	(3) TFP 3-month change (Util. Adj.)
Y=Wage Growth	-0.011	-0.003	-0.004
	(0.013)	(0.008)	(0.009)
Observations	136	136	136
R^2	0.013	0.001	0.002

Notes: Table shows results from a regression of 3-month ECI wage changes on labor productivity and TFP 3-month changes. Newey-West standard errors in parentheses.

wage growth.

3.3 Industry Analysis

We next analyze how wage growth correlates with labor market tightness measures in industry-level panel data. Several recent papers have used rich cross-sectional data to learn about aggregate relationships, e.g., Hazell et al. (2022) and Barnichon and Shapiro (2024). In principle, the correlations we uncovered in the previous section could be driven by other variables that happen to be correlated with quits and V/ES, rather than by the relationships in the model. If that were the case, we could not be sure that the superior performance of quits and V/ES in explaining wage growth will continue to hold going forward. By better understanding the variation at the industry level, we can both further test the mechanism of our model and understand the explanatory power within industries as well as aggregate.

We run similar regressions as equation (5) at the industry-level:

$$\Pi^w_{it} = \beta_1 X_{it} + \gamma_i + \rho_t + \epsilon_{it}, \tag{9}$$

where i indexes the industry, t indexes the quarter, Π^w_{it} is 3-month ECI wage growth, X_{it} is a labor market variable of interest, and γ_i and ρ_t are industry and time fixed effects, respectively.

We obtain industry-level employment and unemployment data from the CPS for 11 broad sectors, and retrieve the hires rate and quits rate, job openings, and hires per vacancies from JOLTS.[9] The time period considered is now 2001:q1-2024:q2 due to the availability of industry-level JOLTS data. We construct the jobs-workers gap as the difference between vacancies and unemployment, normalized by the sum of employed and unemployed. We generate the job finding rate and the separation rate from the CPS for each of the sectors. Since we do not have granular information on

[9]The 11 sectors covered are Construction, Manufacturing, Wholesale Trade, Retail Trade, Information, Financial Services, Professional and Business Services, Education and Health Services, Leisure and Hospitality, and Other Private Services.

Table 5: Industry-Level Wage Growth Regressions

Measure X_t	**Coefficient on X_t**	**Within Fit**
Quits Rate	0.23	0.019
V/ES	0.13	0.010
Hires Rate	0.10	0.005
Jobs-Workers Gap	0.07	0.004
Unemployment Rate	-0.06	0.003
Separation Rate	-0.05	0.002
Vacancy/Hire	0.03	0.001
V/U	0.01	0.000
Job Finding Rate	-0.00	0.000

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, while "Fit" reports the within R-squared value from the panel regression (9): $\Pi^w_{it} = \beta_1 X_{it} + \gamma_i + \rho_t + \epsilon_{it}$. All measures of tightness are ordered by their fit. Estimates use data from 2001:Q1–2024:Q2. Definitions of all measures can be found in Appendix A, except for V/ES which for industry measures uses $ES = U + 0.14E$. Underlying OLS regressions can be found in Appendix C.

nonemployed workers by industry, we are not able to compute V/ES in the same way as above. Instead, we define effective searchers as $ES = 0.14E + U$, where the weight $\lambda_{EE} = 0.14$ is the one used in the calibration of Bloesch, Lee, and Weber (2024). The NFIB Difficulty Hiring measure, CB Jobs Availability, Acceptance Rate, and continuing claims are not available for disaggregated sectors. As before, we normalize all right-hand side variables to have mean zero and standard deviation of one. We present the regression results in Table 5 in the same way as above and show the standardized regression coefficient and the within R-Squared (fit) for each variable. The detailed regression results are in Appendix C.

The results indicate that the quits rate and V/ES are the variables most strongly correlated with wage growth within industries, consistent with the aggregate findings and the model. A one standard deviation increase in the quits rate (0.93) translates into about 0.23 percentage points higher wage growth. A one standard deviation rise in V/ES (0.11) is associated with 0.13 percentage points higher wage growth. The other measures of tightness are less correlated with wages. Note that the unemployment rate and V/U may perform poorly because the unemployment rate might not be well-measured at the industry-level since workers can switch across industries.

We next run bivariate regressions, where we regress wage growth on both the quits rate as the variable most strongly correlated with wage growth and on one of the other measures, to examine whether these measures have additional explanatory power once quits are accounted for. Table 6 shows that in all regressions, quits retain strong explanatory power. Beyond quits, V/ES has the highest explanatory power for wage growth, again similar to the aggregate results. All other variables add relatively little.

In Appendix C.2, we also evaluate the effect of TFP shocks at the industry level empirically

Table 6: Bivariate Industry-Level Regressions: Quits and Others

Measure X_t	**Coefficient on X_t**	**Quits Coefficient**	**Within Fit**
V/ES	0.08	0.20	0.023
Separation Rate	-0.06	0.23	0.022
Jobs-Workers Gap	0.04	0.21	0.020
Unemployment Rate	-0.04	0.22	0.020
Vacancy/Hire	0.06	0.24	0.021
V/U	0.02	0.23	0.019
Hires Rate	0.01	0.22	0.019
Job Finding Rate	-0.01	0.23	0.019

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, while "Fit" reports the within R-squared value from the panel regression (9): $\Pi_{it}^{w} = \beta_1 X_{it} + \beta_2 Q_{it} + \gamma_i + \rho_t + \epsilon_{it}$. All measures of tightness are ordered by their fit. Estimates use data from 2001:Q1–2024:Q2. Definitions of all measures can be found in Appendix A, except for V/ES which for industry measures uses $ES = 0.14E + U$. Underlying OLS regressions can be found in Appendix C.

and find some evidence of a modest positive effect of productivity on industry-level wages. This is not inconsistent with the aggregate results: even if monetary policy does not respond to industry-specific TFP shocks, consumer's demand for the output of the affected industry will rise if optimizing firms lower prices. If demand rises by enough, then firms will need more workers to meet demand in spite of the increase in TFP, leading them to post more vacancies and to pay higher wages. As a result, a transitory, industry-specific TFP shock and industry-specific wages can be positively correlated, even if this relationship is small or absent in the aggregate.

4 Applications: An Index and Forecasting

The previous analysis has highlighted that – in both aggregate data and industry-level panel data – the quits rate and V/ES are most strongly correlated with wage inflation amongst a broad range of widely-used labor market tightness measures. Building on this insight, we now develop a parsimonious index of labor market tightness that combines the quits rate and V/ES. We then perform forecasting regressions and out-of-sample predictions of wage growth using our new index, quits, and V/ES. We show that our new index and the quits rate are the best out-of-sample predictors of wage growth among all variables considered.

4.1 An Index for Wage Growth

We generate a labor market tightness index that uses as inputs the coefficients of our regression of 3-month growth on quits and V/ES. This index is a useful visual summary of our findings. It is motivated by the following observations: (1) the model predicts that either quits or V/ES

is nearly a sufficient statistic for wage growth; (2) in practice, these two indicators track wage growth the best contemporaneously among a variety of indicators, as seen in Table 1; (3) both of these indicators are likely noisy measures of their theoretical counterparts, and combining them may add useful information compared to using the measures separately. To construct the index, we take a weighted average across the quits rate and V/ES, using as weights the fitted values from the regression underlying the first row of Table 2, which estimated the correlation of each of these indicators with wage growth. We refer to this index as the *Heise-Pearce-Weber (HPW) Tightness Index*. As for all other variables, we normalize this measure to have mean zero and standard deviation of one. Appendix E provides details on the exact construction of the index.

Figure 2 demonstrates the fit of the HPW Index visually by plotting it against 3-month wage growth, normalized to have mean of zero and variance of one. The two series are highly correlated with a correlation of 0.9. The HPW index performs particularly well during the pandemic period, 2020:Q1—2022:Q4, shaded in grey. At the peak of the post-pandemic inflation, the index predicted wage growth of about 2.6 standard deviations above the mean, equivalent to a 3-month wage growth of 1.3 percent, close to the observed values. Overall, the index is thus a useful metric to track wage growth and visualize wage pressures.

4.2 Forecasting Wage Growth

Policymakers are interested in forecasting the path of wage inflation in the future to calibrate the appropriate stance of policy. We therefore next examine how well the HPW Index, the quits rate, and V/ES predict wage growth one, two, or four quarters ahead. We compare these against our broad set of tightness measures, asking, what is the effect of tightness today on wage growth tomorrow? We run similar regressions in aggregate data as above using future wage growth as left-hand side variable, and compare the performance of our tightness measures to the alternative variables. We first perform forecasts *in sample*, and turn to out-of-sample forecasts in the next section.

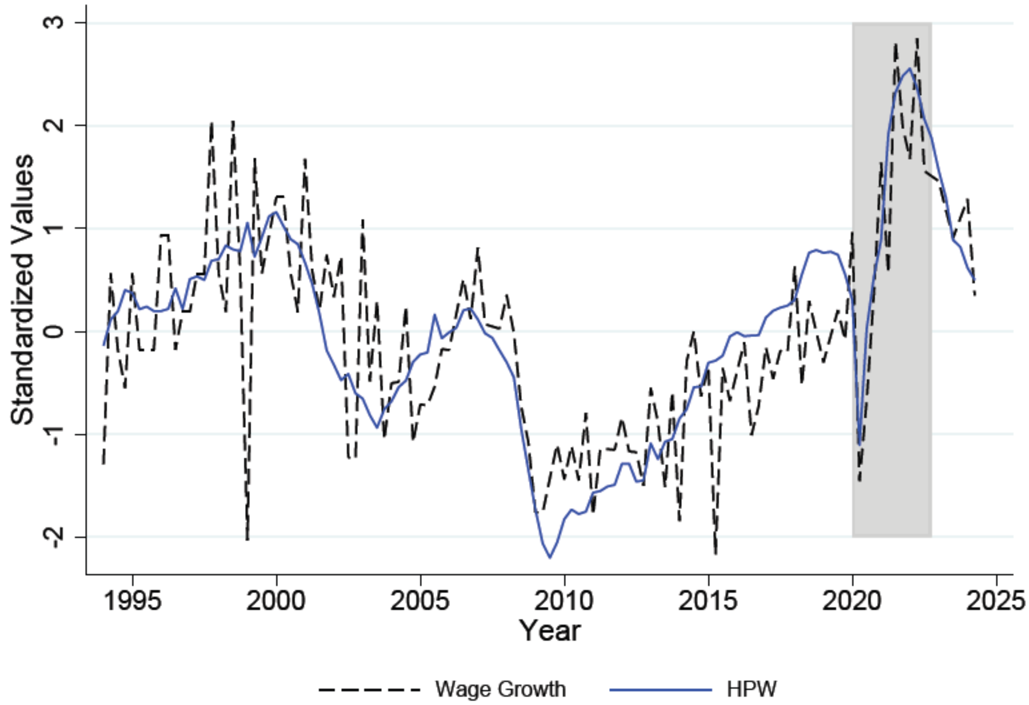
Our specification is a version of our baseline regression (5) that extends forward h periods:

$$\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{10}$$

where $\Pi^w_{t,t+h}$ denotes wage inflation between quarter t and quarter $t+h$, X_t represents our labor market indicator of interest in quarter t, and ϵ_t captures the forecast error term. We focus on $h = 1, 2,$ and 4 quarter ahead wage growth. This enables us to test our forecasting fit against other commonly used labor market measures.

Table 7 analyzes the fit of our measures alongside the other standard measures in the one, two, and four quarter ahead (year-over-year) wage growth regressions; regression tables with Newey-

Figure 2: HPW Index vs. 3-Month Wage Growth



Notes: The HPW Index is computed as a weighted average of the quits rate and V/ES, where the weights are obtained from the first row of Table 2. HPW has been normalized to have mean zero and standard deviation of one. Wage growth is measured using the 3-month log change in the ECI for salaries and wages of private industry workers, normalized to have mean zero and standard deviation of one. Covid period and recovery 2020:Q1—2022:Q4 is shaded.

West standard errors can be found in Appendix B Tables A.4, A.5, and A.6. We rescale the wage changes for the two-quarter and four-quarter ahead regressions into quarterly growth rates so that the regression coefficients are comparable across horizons.

We find that out of all measures tested, the HPW measure fits wage inflation the best over all forecasting horizons. A one standard deviation increase in the HPW Index (by 0.21) is associated with an increase in wage growth of 0.22, 0.21, and 0.20 percentage points over the next one, two, and four quarters. The second-best measure over all three horizons is the quits rate on its own. A one standard deviation increase in the quits rate (by 0.39) is associated with wage growth of 0.20, 0.20, and 0.19 percentage points respectively for next one, two, and four quarters. The V/ES measure is the third-best predictor over all horizons. All other commonly used measures of labor market tightness have lower fit and lower standardized coefficients in absolute value. We find the same pattern when we control for current period wage growth in Appendix D.

Table 7: Future Wage Growth Regressions

	1Q Ahead		2Q Ahead		4Q Ahead	
Variable	Coef.	Fit	Coef.	Fit	Coef.	Fit
HPW	0.22	0.62	0.21	0.74	0.20	0.77
Quits Rate	0.20	0.59	0.20	0.72	0.19	0.77
V/ES	0.19	0.50	0.19	0.59	0.18	0.61
Conference Board Jobs Availability	0.17	0.40	0.16	0.49	0.16	0.53
NFIB Difficulty Hiring	0.17	0.39	0.17	0.51	0.17	0.56
Jobs-Workers Gap	0.17	0.39	0.16	0.46	0.15	0.47
V/U	0.16	0.37	0.16	0.45	0.15	0.45
Job Finding Rate	0.15	0.31	0.14	0.38	0.13	0.36
Acceptance Rate	-0.16	0.31	-0.16	0.38	-0.15	0.41
Unemployment Rate	-0.14	0.27	-0.13	0.30	-0.11	0.27
Hires Rate	0.13	0.23	0.13	0.32	0.14	0.39
Vacancy/Hire	0.10	0.15	0.10	0.18	0.10	0.19
Continuing Claims	-0.09	0.11	-0.08	0.11	-0.06	0.08
Separation Rate	-0.03	0.01	-0.02	0.01	-0.01	0.00

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, while "Fit" reports the R-squared value from the simple univariate time-series regression (5): $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t$, where h =1, 2, or 4. Wage changes for the two-quarter and four-quarter ahead regressions are rescaled into quarterly growth rates. All measures of tightness are ordered by their fit in the "1Q Ahead" regressions. Estimates use data from 1990:Q2–2024:Q2, when quits data are available, or shorter horizons where less data are available. Definitions of all measures can be found in Appendix A; underlying OLS regressions can be found in Appendix B Tables A.4, A.5, and A.6

4.3 Out-of-Sample Forecasts

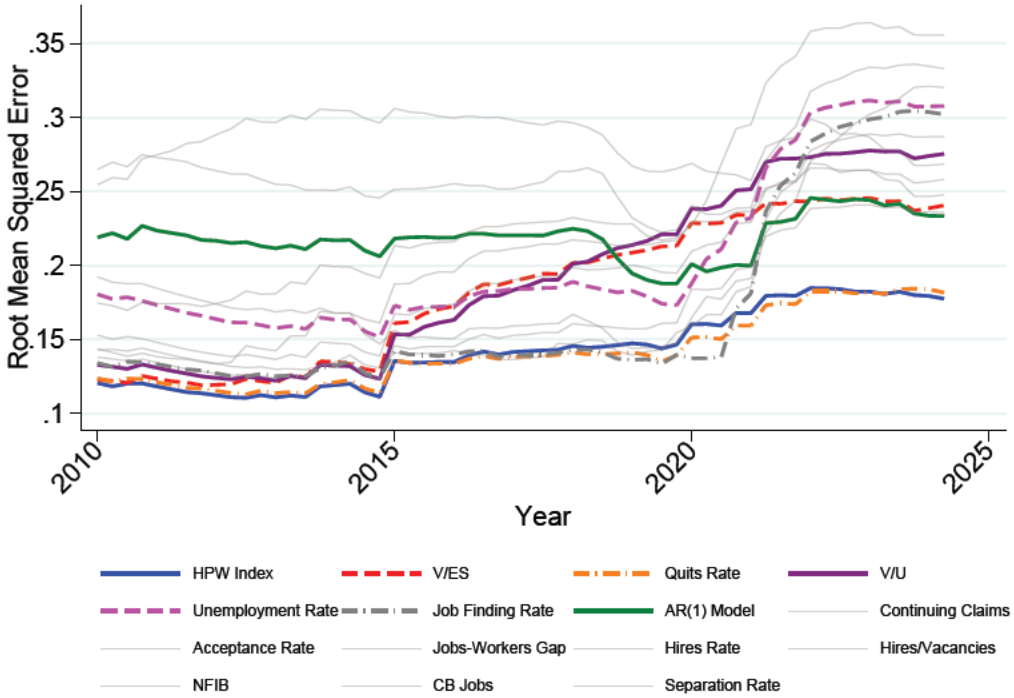
While the previous section has shown that the HPW Index, the quits rate, and V/ES predict wage growth well in sample, a more stringent test of these metrics is whether they can forecast wage growth with only the available data at a given point in time, i.e., out-of-sample. We therefore perform out-of-sample one-quarter ahead forecasts of wage growth for each of the tightness measures and compare the root-mean-squared-error (RMSE) of the forecasts across the different variables.

Our methodology computes the predicted value of wage growth in quarter $t+1$ from the following one-quarter ahead wage growth regression model:

$$\Pi^w_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_t \text{ for } t < T. \quad (11)$$

where in contrast to before we only use data from the start of our sample to quarter T. This regression delivers a predicted value $\hat{\Pi}^w_{T+1}$. Given that our first data point for the HPW Index is in 1994Q1, we start with 40 quarters of data to run our first regression for T =2003Q4 (Estimation period: 1994Q1–2003Q4), predicting out-of-sample the wage growth in 2004Q1. We then roll our methodology forward to T =2004Q1, estimate the model for 1994Q1–2004Q1, and predict the wage growth for 2004Q2. We continue producing forecasts up until the last quarter 2024Q1.

Figure 3: Forward Wage Growth on Different Measures, $RMSE$



Notes: Figure plots the RMSE over 40-quarter rolling windows from one-period ahead out-of-sample 3-month wage changes from the ECI starting in 2004Q1 against the HPW index and other labor market indicators. For ease of reading, we only add color to V/ES, quits, V/U, unemployment, the job finding rate, and the AR(1) model.

For each quarter, we compute the difference between our predicted wage growth and the ex-post realized wage growth. We then compute the RMSE in a rolling manner over 40 quarter windows, starting with 2010Q1. For the first four years, we take a smaller window due to data limitations as the out-of-sample forecast starts in 2004Q1.

Our methodology seeks to generate forecasts in the same way a policymaker would do it, using only the available data up to a specific time period. Importantly, this restriction means that we cannot compute the HPW Index using the weights on the quits rate and on V/ES from Table 2, since that table used the entire sample period. Instead, we re-compute the HPW Index in each quarter by running regression (6) with the quits rate and V/ES using the data available up to that point, obtaining the regression coefficients, and using these coefficients as weights to construct the HPW Index.

We plot the RMSE associated with the rolling window ending in quarter t for each of our tightness measures in Figure 3. As a benchmark, we compute the RMSE also for a simple AR(1) model for wage inflation (green line). The figure shows that prior to the COVID period, quits and the HPW Index were both the measures with the lowest RMSE but close to the other measures.

V/U does a relatively good job in forecasting wage growth until 2015, but then begins to separate. In 2020, quits and HPW further separate from others that have their forecast errors spike, while V/ES does a better job than V/U. The steady deterioration in the forecasting performance of both vacancy-based measures aligns with other work finding that the relationship between vacancies and other labor market variables appears to have shifted over time (e.g., Mongey and Horwich, 2023). Among all our indicators, only quits and HPW consistently outperform the simple AR(1) model.

The good performance of the AR(1) model motivates us to examine the robustness of some our results to the inclusion of lagged wage growth in our regressions, in addition to our labor market tightness measures. Appendix D shows that allowing for current wage growth to directly affect future wage growth in the regressions underlying the forecasting regressions in Figure 3 does not alter the results.

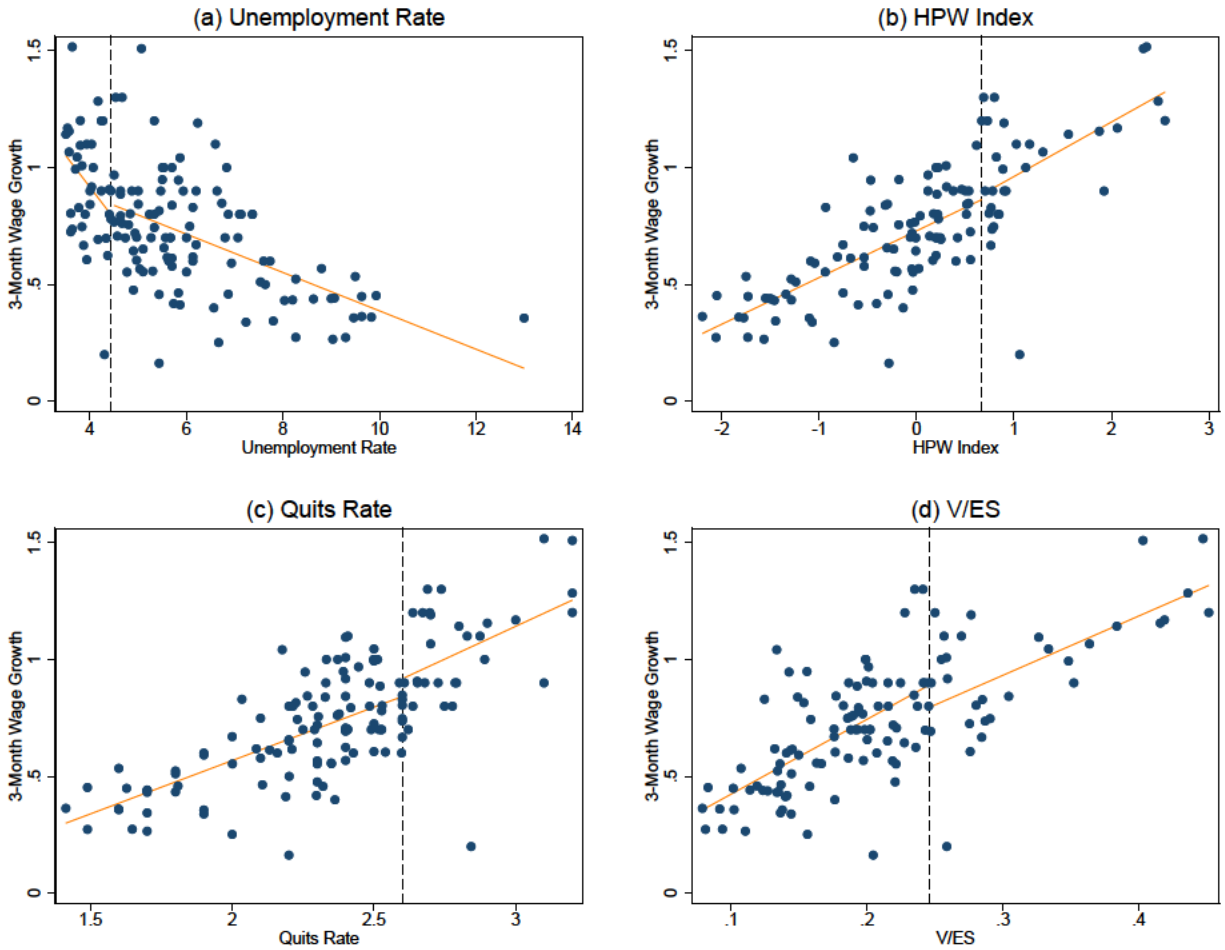
Overall, these results are consistent with our main empirical exercises and the model's implication that on-the-job search plays a central role in tracking and forecasting nominal wage growth. Towards the end of our sample, we note that HPW modestly outperforms even quits in forecasting wage inflation in Figure 3. Our findings suggest that the HPW Index and the quits rate are the best predictors of wage growth in the next quarter.

5 Nonlinearity in the Wage Phillips Curve

As the previous section has shown, the forecasting performance of several standard measures of labor market tightness deteriorated sharply in the post-COVID period, when wage inflation surged. This result raises the question of whether there is a nonlinear relationship between wage growth and labor market tightness, which led to a jump in wage inflation once a threshold was crossed. As discussed in our introduction, it is common in the literature to study nonlinearities in price Phillips curves in terms of unemployment rates (e.g., Cerrato and Gitti, 2022) or V/U (e.g., Crust et al., 2023; Gitti, 2024; Benigno and Eggertsson, 2024). We here consider nonlinearities in the wage Phillips curve with respect to unemployment as well as with respect to the measures we find most strongly correlate with wage growth in practice: the HPW index, quits, and V/ES.

Panel (a) of Figure 4 presents a scatterplot of the average quarterly unemployment rate against 3-month ECI wage growth over our sample period. To provide a visual intuition of a potential nonlinearity, we add fit lines from a linear regression when unemployment is below the 25th percentile, hence the labor market is very tight, and when unemployment is above the 25th percentile. Consistent with earlier work suggesting that the wage Phillips curve is nonlinear in unemployment going back to Phillips (1958), and examined empirically by, e.g., Hooper, Mishkin, and Sufi (2020), we find some evidence of nonlinearity in the wage Phillips curve. The slope seems to be somewhat

Figure 4: Nonlinearity in the Tightness - Wage Growth Relationship



Notes: Figures plot 3-month wage changes from the ECI for the period 1990:q2-2024:q2 against the unemployment rate, the HPW index, the quits rate, and V/ES.

steeper when the labor market is tight, suggesting a greater effect of changes in unemployment on wage inflation in such periods.

We next turn to the HPW Index in panel (b), the quits rate in panel (c), and V/ES in panel (d). These measures indicate a tight labor market when they are high, and so we fit linear regressions when they are above and below the 75th percentile. These figures do not suggest a strong nonlinearity with respect to any of the variables.

We next evaluate the presence of nonlinearities more formally. First, we run regressions of 3-month wage growth on the tightness measures similar to equation (5), but add a threshold term that allows for a change in the relationship between wage growth and the tightness measure when the labor market is very tight:

$$\Pi_t^w = \beta_0 + \beta_1 \mathbb{I}(X_t > \gamma) + \beta_2 X_t + \beta_3 \mathbb{I}(X_t > \gamma) \cdot X_t + \epsilon_t. \tag{12}$$

Table 8: Nonlinearities in Wage Growth Regressions

	Baseline Regression	Threshold Regression	Squared Regression
Measure X_t	Fit	Fit	Fit
Unemployment Rate	0.34	0.36	0.35
HPW	0.60	0.60	0.60
Quits	0.55	0.56	0.56
V/ES	0.52	0.57	0.52

Notes: Table shows results from regressions of 3-month wage changes from the ECI. "Fit" reports the R-squared value. Column 1 reports fit from regression (5): $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Column 2 reports fit from regression (12): $\Pi_t^w = \beta_0 + \beta_1 \mathbb{I}(X_t > \gamma) + \beta_2 X_t + \beta_3 \mathbb{I}(X_t > \gamma) \cdot X_t + \epsilon_t$. Column 3 reports fit from regression: $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \epsilon_t$. Estimates use data from 1990:Q2–2024:Q2, when quits data are available, or shorter horizons in the few cases where less data are available. Definitions of all measures are in Appendix A; underlying OLS regressions with Newey-West standard errors are in Appendix F Table A.11.

Here, γ is the structural break point (the 25th percentile for unemployment and the 75th percentile for the other variables), and X_t is the tightness measure of interest normalized to have mean zero and standard deviation of one. In our second analysis, we add a quadratic term to the wage growth regressions (5).

Table 8 presents the results. Similar to before, we evaluate whether the fit of wage growth, measured by R-squared, improves when we add these extra terms. The first column of Table 8 restates the fit from the regression without nonlinear terms from Table 1. The second column shows the fit once we include the additional threshold terms from regression (12). The fit improves marginally for all variables, rising from 0.34 to 0.36 for the unemployment rate, with the largest improvement for V/ES. In Appendix F, we show that this improvement is solely due to a level shift in the fit line, which can also be seen in panel (d) above, while the slope of the wage-tightness relationship is basically unchanged across the entire range of tightness. The third column of Table 8 illustrates that adding a quadratic term essentially does not change the fit for all variables. Thus, we do not find much evidence for nonlinearities. Our findings suggest that based on our measures of labor market tightness there is nothing unusual in the wage/tightness relationship, even during the period of extreme tightness in the aftermath of COVID.

6 Conclusion

Measuring labor market tightness is an important question in academia and in public policy. In this paper, we build on the insight that incorporating the decisions of both unemployed and employed workers is essential for a comprehensive measure of tightness. Amongst a broad range of measures of labor market tightness, quits and vacancies per effective searcher are independently the most strongly correlated with wage growth—both in the aggregate time series and in within-industry panel regressions. This is consistent with the importance of capturing activity *on-the-job* as being essential for measuring labor market tightness.

Based on our findings, we develop the HPW composite index of wage growth, using quits and V/ES. This index closely tracks wage inflation both pre- and post-Covid. We then demonstrate that the HPW Index predicts wage growth best both in and out-of-sample, though its performance is similar to the quits rate on its own. Our findings are consistent with the predictions of a New Keynesian DSGE model that incorporates a frictional labor market with on-the-job-search, developed in Bloesch, Lee, and Weber (2024). Consistent with that model, transitory productivity shocks have an ambiguous effect on wage growth. We find little evidence of any meaningful nonlinearity in the wage Phillips curve.

Our findings and the new tightness index can be useful for policymakers to assess the state of the labor market and to calibrate the stance of monetary policy. One question for future research is the coexistence of the apparently nonlinear price Phillips curve and the approximately linear wage Phillips curve. This finding is consistent with firms varying their pass-through of wage pressures into prices dependent on the state of the labor market, as documented by Amiti et al. (2024). We leave a formal to attempt to rationalize these findings to future work.

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Appendix

The Appendix provides more details on data sources and construction, expands on the specifications in the main text, and performs further robustness on the core messages. Appendix A discusses each labor market indicator by their source, definition, and time period used in the paper. Appendix B reports the full regressions from the main text with standard errors and observations. Appendix C expands on industry-level regressions in the main text, in addition to reporting regressions of wage growth at the industry-level against productivity growth. Appendix D shows that the results from the forecasting regressions are robust to including lagged wage growth. Appendix E reports in detail the construction of the HPW Index to enable other researchers and interested readers to produce the measure. Finally, Appendix F reports the full regression results from the nonlinear regressions.

A Definition of Labor Market Tightness Variables

In this section, we define in more detail the labor market tightness indicators discussed in the main text and provide information on the sample period for which they are available.

- **Job finding rate**: Source: CPS. This measure is the rate with which unemployed workers find jobs, computed using the CPS worker flows as in Shimer (2012). Availability: 1990q2-2024q2.

- **Continuing claims**: Source: U.S. Employment and Training Administration via Haver Analytics. This measure is the number of continuing claims for unemployment insurance, averaged across weeks in the month. Availability: 1990q2-2024q2.

- **Acceptance Ratio (AC)**: Source: Fujita, Moscarini, and Postel-Vinay (2024). This measure is computed as the job-to-job transition rate divided by the unemployment-to-employment transition rate. Moscarini and Postel-Vinay (2023) argue that this is a good measure of labor market slack. A high rate of job-to-job transitions relative to the rate of unemployment-to-employment transitions suggests that workers are relatively misallocated as they are still frequently moving between jobs. Availability: 1995q4-2024q2.

- **Jobs-workers gap**: Source: BLS. This measure is defined as (Vacancies – unemployment)/Labor force. A high workers' gap suggests that there are many vacancies compared to unemployed workers and hence the labor market is relatively tight. Availability: 1990q2-2024q2.

- **V/ES** Source: BLS. This measure is defined as vacancies / effective searchers, where effective searchers are defined as $ES = U_s + 0.48 \cdot U_l + 0.4 \cdot Z^{\text{want}} + 0.09 \cdot Z^{\text{do not want}} + 0.07N$, where U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, Z^{want} is the share of workers not in the labor force that want to work, $Z^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and N is the share of employed workers. The weights on these terms reflect the relative search intensities of these workers estimated by Abraham, Haltiwanger, and Rendell (2020) and translated to more readily avaialble data by Şahin (2020). Short-term unemployed, U_s, are those 16 and older that have been unemployed for less than 27 weeks. Long-term unemployed, U_l, are those 16 and older that have been unemployed for at least 27 weeks. Z^{want} are marginally attached workers 16 years and older and $Z^{\text{do not want}}$ are workers not in the labor force that are not marginally attached; these can be computed from CPS data beginning in 1994. Vacancies are from JOLTS for 2001:q1-2024:q3 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1990:q2-2000:q4. Availability: 1994q1-2024q2.

- **Hires rate**: Source: BLS, Davis et al. (2012). This is the ratio of hires to total employment in a given period. The hires rate for private sector workers is from JOLTS for 2001:q1-2024:q2 and from the data by Davis et al. (2012) for 1990:q2-2000:q4. Availability: 1990q2-2024q2.

- **Quits rate**: Source: BLS, Davis et al. (2012). This is the ratio of private quits to total employment in a given period. The quits rate is from JOLTS for 2001:q1-2024:q2 and from the data by Davis et al. (2012) for 1990:q2-2000:q4. Availability: 1990q2-2024q2.

- **Vacancies/Hires ratio:** Source: BLS, Davis et al. (2012), Barnichon (2010). This is a measure of the job filling rate for firms, computed job openings divided by hires. When this ratio is high, it means the duration of a vacancy is high, and the labor market is tight. Vacancies are from JOLTS for 2001:q1-2024:q3 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1990:q2-2000:q4. The hires rate for private sector workers is from JOLTS for 2001:q1-2024:q2 and from the data by Davis et al. (2012) for 1990:q2-2000:q4. Availability: 1990q2-2024q2.

- **NFIB Difficulty Hiring:** Source: NFIB via Haver Analytics. This measure is based on a survey of small businesses asking them whether they have few or no qualified applicants for job openings. It is a measure of small businesses' perceptions of worker availability. Availability: 1993q2-2024q2.

- **Conference Board (CB) jobs availability**: Source: Conference Board via Haver Analytics. This is the percentage of consumers who think jobs are plentiful to get minus the percentage who believe that jobs are hard to get (Jobs Plentiful – Jobs Hard to Get). Availability: 1990q2-2024q2.

- **Separation rate**: Source: CPS. This measure is the rate at which individuals are separated from their jobs, computed using the CPS worker flows as in Shimer (2012). This measure combines quits (voluntary exit) and layoffs (involuntary exit). Availability: 1990q2-2024q2.

B Reduced Form Wage Phillips Curve Estimates

This section presents the detailed regression tables underlying the results in Tables 1 - 3 and Table 7 of the main text. We do not present these tables in the main text given the persistence of the variables involved, and hence the difficulty of computing standard errors. Nevertheless, we present the regression tables with Newey-West standard errors (with 4 lags on the quarterly data) here for complete information.

Table A.1 shows the results from running equation (5) with all variables, each normalized to have mean zero and standard deviation of one. We note that not all of the variables are available for the entire sample period, and thus the number of observations varies. These results underlie Table 1 in the main text.

Table A.1: Contemporaneous Wage Growth Regressions with Tightness Measures

	(1)	(2)	(3)	(4)	(5)
Indep. Var	Quits Rate	V/ES	V/U	Unemployment Rate	Job Find. Rate
Y=Wage Growth	0.200***	0.199***	0.172***	-0.158***	0.155***
	(0.015)	(0.016)	(0.022)	(0.024)	(0.021)
Observations	137	122	137	137	137
R^2	0.551	0.517	0.406	0.341	0.330
	(6)	(7)	(8)	(9)	(10)
Indep. Var	Cont. Claims	Acceptance Rate	Jobs-Workers Gap	Hires Rate	Vacancy/Hire
Y=Wage Growth	-0.117***	-0.156***	0.178***	0.124***	0.104***
	(0.039)	(0.026)	(0.023)	(0.028)	(0.035)
Observations	137	115	137	137	137
R^2	0.187	0.304	0.436	0.211	0.148
	(11)	(12)	(13)		
Indep. Var	NFIB Diff. Hiring	CB Jobs Availability	Separation Rate		
Y=Wage Growth	0.175***	0.170***	0.004		
	(0.026)	(0.029)	(0.037)		
Observations	125	137	137		
R^2	0.408	0.399	0.000		

Notes: Table shows results from a regression of annualized 3-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

We find that all labor market indicators, except for the separation rate, are strongly correlated with wage growth. Importantly, the results indicate that the quits rate and the ratio of vacancies over effective searchers, V/ES, have the greatest standardized coefficients (0.200 and 0.199, respectively) and R-squared coefficients (0.551 and 0.517, respectively). Thus, while each of the

Table A.2: Bivariate Wage Growth Regressions with Tightness Measures and Quits

		(2)	(3)	(4)	(5)
Indep. Var		V/ES	V/U	Unemployment Rate	Job Find. Rate
Y=Wage Growth		0.079**	0.042	0.003	0.006
		(0.031)	(0.030)	(0.031)	(0.027)
Quits Rate		0.137***	0.168***	0.203***	0.195***
		(0.026)	(0.024)	(0.029)	(0.030)
Observations		122	137	137	137
R^2		0.600	0.561	0.551	0.552
	(6)	(7)	(8)	(9)	(10)
Indep. Var	Cont. Claims	Acceptance Rate	Jobs-Workers Gap	Hires Rate	Vacancy/Hire
Y=Wage Growth	0.001	0.024	0.018	-0.005	0.019
	(0.021)	(0.022)	(0.043)	(0.026)	(0.023)
Quits Rate	0.201***	0.219***	0.184***	0.203***	0.192***
	(0.019)	(0.022)	(0.038)	(0.025)	(0.015)
Observations	137	115	137	137	137
R^2	0.551	0.598	0.553	0.552	0.555
	(11)	(12)	(13)		
Indep. Var	NFIB Difficulty Hiring	CB Jobs Availability	Separation Rate		
Y=Wage Growth	0.007	-0.008	0.026		
	(0.035)	(0.036)	(0.018)		
Quits Rate	0.194***	0.207***	0.203***		
	(0.030)	(0.034)	(0.017)		
Observations	125	137	137		
R^2	0.574	0.552	0.561		

Notes: Table shows results from a regression of 3-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Independent variables (outside of quits rate) are listed at the top of the column. Newey-West standard errors are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

alternative indicators provide insights, the measurements implied by the structural model track wage growth best.

Given the strong performance of quits, we next run bivariate regressions where we add the quits rate to one of the other labor market tightness indicator variables, and re-run the regressions similarly to before.[10] These regressions underlie the results in Table 2 in the main text.

Table A.2 shows that quits holds up as the strongest indicator, and that in most regressions the coefficient on the other variable drops to effectively zero, with the notable exception of V/ES. The results suggest that once the quit rate is accounted for, there is little additional information in other indicators of labor market tightness.

We next report the full specification from Table 3 in the main text in Table A.3. We further find the importance of quits and V/ES in tracking 12-month wage growth.

We now turn to the three sets of regressions in Table 7 that forecast wage growth in the next one, two, and four quarters respectively with all indicators on the right-hand side, including the HPW measure. Tables A.4, A.5, and A.6 report these regressions respectively with our 14 labor market indicators, which includes the HPW index. We again find consistently that quits and HPW outperforms other measures, with HPW always with a higher coefficient than all others, and only

[10]We do not add all variables simultaneously as regressors since the variables are strongly correlated and doing so makes the signs on the individual coefficients hard to interpret.

Table A.3: Current 12-month Wage Growth with Tightness Measures

Indep. Var	(1) Quits Rate	(2) V/ES	(3) V/U	(4) Unemployment Rate	(5) Job Find. Rate
Y=Wage Growth	0.179***	0.180***	0.159***	-0.140***	0.155***
	(0.017)	(0.018)	(0.022)	(0.032)	(0.017)
Observations	137	122	137	137	137
R^2	0.664	0.640	0.525	0.405	0.500
Indep. Var	**(6) Cont. Claims**	**(7) Acceptance Rate**	**(8) Jobs-Workers Gap**	**(9) Hires Rate**	**(10) Vacancy/Hire**
Y=Wage Growth	-0.099**	-0.161***	0.158***	0.119***	0.090**
	(0.042)	(0.024)	(0.026)	(0.027)	(0.037)
Observations	137	115	137	137	137
R^2	0.204	0.486	0.519	0.292	0.167
Indep. Var	**(11) NFIB Diff. Hiring**	**(12) CB Jobs Availability**	**(13) Separation Rate**		
Y=Wage Growth	0.156***	0.154***	0.016		
	(0.027)	(0.030)	(0.038)		
Observations	125	137	137		
R^2	0.492	0.490	0.005		

Notes: Table shows results from a regression of current 12-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

very slightly worse in R^2 than quits on 12-month ahead wage growth.

Table A.4: 3-month Ahead Wage Growth with Tightness Measures

Indep. Var	(1) HPW	(2) Quits Rate	(3) V/ES	(4) V/U	(5) Unemployment Rate
Y=Wage Growth	0.216***	0.205***	0.194***	0.163***	-0.139***
	(0.013)	(0.016)	(0.019)	(0.024)	(0.030)
Observations	122	137	122	137	137
R^2	0.616	0.588	0.498	0.374	0.269
Indep. Var	**(6) Job Find. Rate**	**(7) Cont. Claims**	**(8) Acceptance Rate**	**(9) Jobs-Workers Gap**	**(10) Hires Rate**
Y=Wage Growth	0.150***	-0.090*	-0.158***	0.167***	0.129***
	(0.019)	(0.050)	(0.023)	(0.024)	(0.025)
Observations	137	137	115	137	137
R^2	0.314	0.115	0.313	0.393	0.234
Indep. Var	**(11) Vacancy/Hire**	**(12) NFIB Diff. Hiring**	**(13) CB Jobs Availability**	**(14) Separation Rate**	
Y=Wage Growth	0.103***	0.172***	0.168***	-0.025	
	(0.035)	(0.026)	(0.029)	(0.038)	
Observations	137	125	137	137	
R^2	0.150	0.393	0.395	0.009	

Notes: Table shows results from a regression of 3-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.5: 6-month Ahead Wage Growth with Tightness Measures

	(1)	(2)	(3)	(4)	(5)
Indep. Var	HPW	Quits Rate	V/ES	V/U	Unemployment Rate
Y=Wage Growth	0.211***	0.199***	0.189***	0.157***	-0.128***
	(0.012)	(0.015)	(0.020)	(0.024)	(0.034)
Observations	121	136	121	136	136
R^2	0.738	0.719	0.592	0.445	0.297

	(6)	(7)	(8)	(9)	(10)
Indep. Var	Job Find. Rate	Cont. Claims	Acceptance Rate	Jobs-Workers Gap	Hires Rate
Y=Wage Growth	0.144***	-0.078	-0.156***	0.160***	0.133***
	(0.020)	(0.055)	(0.020)	(0.025)	(0.023)
Observations	136	136	114	136	136
R^2	0.377	0.111	0.384	0.463	0.318

	(11)	(12)	(13)	(14)
Indep. Var	Vacancy/Hire	NFIB Diff. Hiring	CB Jobs Availability	Separation Rate
Y=Wage Growth	0.102***	0.173***	0.164***	-0.023
	(0.034)	(0.025)	(0.028)	(0.036)
Observations	136	124	136	136
R^2	0.184	0.509	0.488	0.009

Notes: Table shows results from a regression of 6-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Dependent variables are adjusted to match 3-month growth rates consistent with the main indicators. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.6: 12-month Ahead Wage Growth with Tightness Measures

	(1)	(2)	(3)	(4)	(5)
Indep. Var	HPW	Quits Rate	V/ES	V/U	Unemployment Rate
Y=Wage Growth	0.201***	0.190***	0.182***	0.150***	-0.114***
	(0.013)	(0.013)	(0.022)	(0.025)	(0.037)
Observations	119	134	119	134	134
R^2	0.768	0.769	0.608	0.450	0.271

	(6)	(7)	(8)	(9)	(10)
Indep. Var	Job Find. Rate	Cont. Claims	Acceptance Rate	Jobs-Workers Gap	Hires Rate
Y=Wage Growth	0.129***	-0.061	-0.152***	0.151***	0.137***
	(0.024)	(0.060)	(0.017)	(0.025)	(0.020)
Observations	134	134	112	134	134
R^2	0.356	0.076	0.411	0.465	0.390

	(11)	(12)	(13)	(14)
Indep. Var	Vacancy/Hire	NFIB Diff. Hiring	CB Jobs Availability	Separation Rate
Y=Wage Growth	0.099***	0.170***	0.160***	-0.013
	(0.034)	(0.024)	(0.026)	(0.033)
Observations	134	122	134	134
R^2	0.188	0.556	0.530	0.003

Notes: Table shows results from a regression of 12-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Dependent variables are adjusted to match 3-month growth rates consistent with the main indicators. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

C Industry-Level Regressions

This section focuses on industry-level regressions. We first expand on the regressions in the main text for Tables 5-6, where we report more details underlying these regressions including observations, standard errors, and fixed effects. We then focus on the relationship between wage growth and productivity at the industry level.

C.1 Expanded Regression Results

Table A.7 shows the regression results associated with regression (9) in the main text. We use Driscoll-Kraay standard errors with one lag to account for potential serial and cross-sectional correlation. Both the quits rate and V/ES have the strongest correlation with wage growth out of all the tightness variables considered.

Table A.8 presents the estimated regression coefficients when we include both the quits rate and on one of the other tightness measures jointly in the regression. In all regressions, the correlation between the quits rate and wage growth remains strong. V/ES provides the most additional explanatory value (i.e., the R-squared is largest in this regression).

Table A.7: Industry-Level Wage Growth Regressions

Indep. Var	(1) Quits Rate	(2) V/ES	(3) Unemployment	(4) V/U	(5) Jobs-Workers Gap
Y= Δ Wage Growth	0.226*** (0.064)	0.126** (0.048)	-0.059* (0.030)	0.010 (0.033)	0.074* (0.039)
Industry FE	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Observations	926	926	926	926	926
Within-R^2	0.019	0.010	0.003	0.000	0.004
Indep. Var	(6) Hires Rate	(7) Hires/Vac.	(8) Job Find. Rate	(9) Separation Rate	(10)
Y= ΔWage Growth	0.105* (0.081)	-0.037* (0.055)	-0.005 (0.033)	-0.051** (0.025)	
Industry FE	Y	Y	Y	Y	
Time FE	Y	Y	Y	Y	
Observations	926	926	926	926	
Within-R^2	0.005	0.002	0.000	0.002	

Notes: Table shows results from a regression of 3-month wage changes from the ECI on variables for the period 2001:q1-2024:q2 at the industry-level. Independent variables are standardized to have zero mean and standard deviation of one. Independent variables are listed at the top of the column. Driscoll-Kraay standard errors with one lag are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.8: Bivariate Industry-Level Wage Growth Regressions

Y= Δ Wage Growth	(1)	(2) V/ES	(3) Unemployment	(4) V/U	(5) Jobs-Workers Gap
First Indep. Var (X_t)		0.084**	-0.038	0.020	0.042
		(0.042)	(0.027)	(0.033)	(0.032)
Quits Rate		0.197***	0.218***	0.228***	0.214***
		(0.058)	(0.066)	(0.065)	(0.063)
Industry FE		Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Observations		926	926	926	926
Within-R^2		0.023	0.020	0.019	0.020
Y= ΔWage Growth	(6) Hires Rate	(7) Hires/Vac.	(8) Job Find. Rate	(9) Separation Rate	(10)
First Indep. Var (X_t)	0.006	-0.038*	-0.014	-0.058**	
	(0.045)	(0.021)	(0.033)	(0.025)	
Quits Rate	0.223***	0.227***	0.228***	0.230***	
	(0.065)	(0.064)	(0.064)	(0.065)	
Industry FE	Y	Y	Y	Y	
Time FE	Y	Y	Y	Y	
Observations	926	926	926	926	
Within-R^2	0.019	0.021	0.019	0.022	

Notes: Table shows results from a regression of 3-month wage changes from the ECI on variables for the period 2001:q1-2024:q2 at the industry-level. Independent variables are standardized to have zero mean and standard deviation of one. Independent variables are listed at the top of the column. Driscoll-Kraay standard errors with one lag are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

C.2 Wages and Productivity at the Industry Level

We expand the analysis of Section 3.2 to the industry-level. We take labor productivity from the BLS at the NAICS 2-digit level, and run similar regressions as before at the industry level. The following equation is reported in Table A.9,

$$\Pi_{it}^{w} = \beta_1 X_{it} + \gamma_i + \rho_t + \epsilon_{it}. \tag{13}$$

We first run the regression without fixed effects and then include industry (γ_i) and time (ρ_t) fixed effects. Given that BLS labor productivity is only available at the annual level, we estimate an annual regression.

Unlike the main text's national regressions, wages show a stronger response to productivity in the industry-level regressions. As can be seen in Column 3, with industry and year controls, a 1% increase in productivity in a year is associated with a 0.15% increase in wages in the industry, significant at the 10% level. This is not inconsistent with the aggregate results: even if monetary policy does not respond to industry-specific TFP shocks, consumer's demand for the output of the affected industry will rise if optimizing firms lower prices. If demand rises by enough, then firms will need more workers to meet demand in spite of the increase in TFP, leading them to post more vacancies and to pay higher wages. As a result, a transitory, industry-specific TFP shock and industry-specific wages can be positively correlated, even if this relationship is small or absent in the aggregate.

Table A.9: ECI and Productivity

	(1) Δ% Wage	(2) Δ% Wage	(3) Δ% Wage
Δ Productivity	0.105*	0.089	0.147*
	(0.046)	(0.057)	(0.063)
Industry FE	No	No	Yes
Time FE	No	Yes	Yes
Observations	131	131	131
R^2	0.053	0.586	0.615
Adj R^2	0.046	0.502	0.515

Table shows results from a regression of annual wage changes from the ECI on measured labor productivity from the BLS. Clustered standard errors at the NAICS 2-digit level.

D Additional Robustness on Forecasting

In this section, we show that the results from the forecasting regressions are robust to including lagged wage growth. In particular, we focus on including current ECI wage growth in our regressions of future wage growth. These show how our main variables of interest provide the best forecasting fit even when controlling for current wage growth. We show this both with simple regressions and in our forecasting exercise, following Figure 3 from the main text.

We start by showing a simple regression of 3-month ahead wage growth on current wage growth and a set of variables of interest. The specification takes the form,

$$\Pi_{t+1}^{w} = \beta_0 + \beta_1 X_t + \beta_2 \Pi_t^{w} + \epsilon_t, \tag{14}$$

where Π_{t+1}^{w} is the three-month ahead wage growth, X_t is the standardized tightness measure of interest, and Π_t^{w} is the current three-month wage growth. Table A.10 presents a set of coefficients on bivariate regressions that includes these X_t variables alongside wage growth at time t.

Table A.10: 3-Month Ahead Wage Growth with Current Wage Growth Controls

Indep. Var	(1) HPW	(2) Quits Rate	(3) V/ES	(4) V/U	(5) Unemployment Rate
Y=Wage Growth $t+1$	0.234***	0.213***	0.167***	0.117***	-0.080***
	(0.024)	(0.023)	(0.028)	(0.025)	(0.030)
Wage Growth t	-0.084	-0.041	0.138	0.269***	0.372***
	(0.076)	(0.075)	(0.099)	(0.095)	(0.124)
Observations	122	137	122	137	137
R^2	0.619	0.589	0.507	0.418	0.363

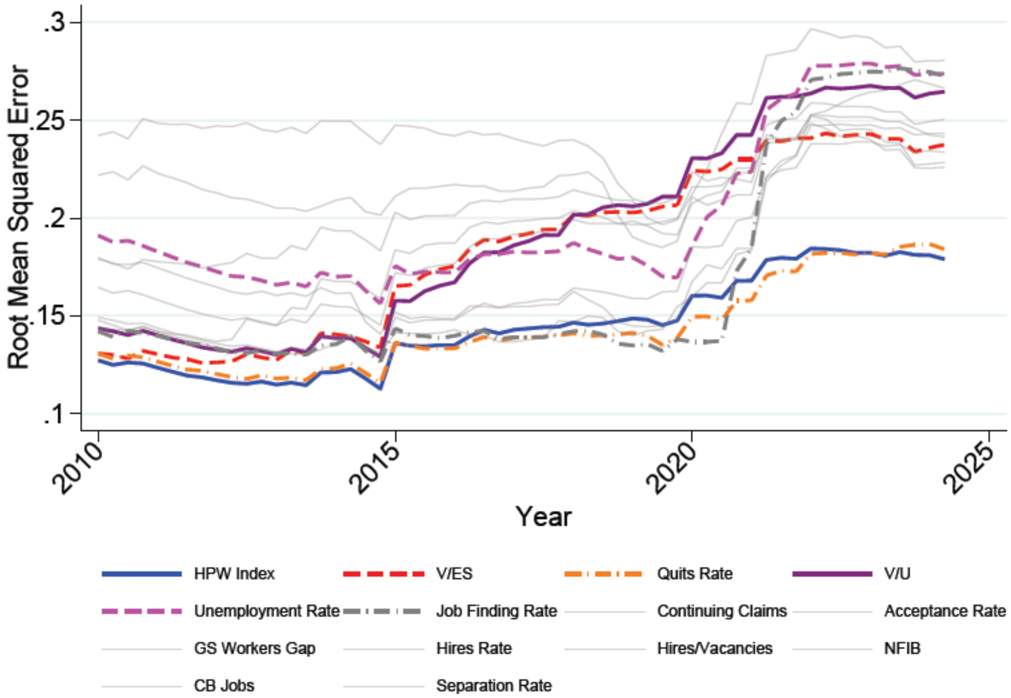
Indep. Var	(6) Job Find. Rate	(7) Cont. Claims	(8) Acceptance Rate	(9) Jobs-Workers Gap	(10) Hires Rate
Y=Wage Growth $t+1$	0.097***	-0.033	-0.095***	0.124***	0.078***
	(0.033)	(0.038)	(0.024)	(0.027)	(0.023)
Wage Growth t	0.338**	0.492***	0.407***	0.241**	0.412***
	(0.166)	(0.118)	(0.129)	(0.101)	(0.131)
Observations	137	137	115	137	137
R^2	0.392	0.316	0.428	0.426	0.371

Indep. Var	(11) Vacancy/Hire	(12) NFIB Diff. Hiring	(13) CB Jobs Availability	(14) Separation Rate
Y=Wage Growth $t+1$	0.055***	0.124***	0.125***	-0.027
	(0.021)	(0.024)	(0.029)	(0.022)
Wage Growth t	0.467***	0.274***	0.253**	0.547***
	(0.086)	(0.089)	(0.101)	(0.094)
Observations	137	125	137	137
R^2	0.340	0.437	0.434	0.314

Notes: Table shows results from a regression of 12-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

We again find that HPW is the strongest indicator in terms of both coefficient size and fit. Both HPW, quits, and V/ES make the knowledge of current wage growth insignificant for predicting future wage growth. However, for all other measures, current wage growth still has important predictive power.

Figure A.1: Forward Wage Growth on Different Measures, $RMSE$



Notes: Figure plots the RMSE from one-period ahead out-of-sample 3-month wage changes from the ECI starting in 2004Q1 against the HPW index and other labor market indicators. All forecasting regressions now also allow for a lagged ECI wage growth term; see text for details. For ease of reading, we only add color to V/ES, quits, V/U, unemployment, and the job finding rate.

We next repeat the out-of-sample forecasting exercise from Figure 3 in the main text, but include the current ECI growth in the model. Specifically, we compute the predicted value of wage growth in quarter $t+1$ from the following one-quarter ahead wage growth regression model:

$$\Pi^w_{t+1} = \beta_0 + \beta_1 X_t + \beta_2 \Pi^w_t + \epsilon_t \text{ for } t < T. \tag{15}$$

where we only use data from the start of our sample to quarter T. This model now includes current wage growth, Π^w_t, as additional predictor. As described in the main text, we compute the MSE over 40-quarter rolling windows. Figure A.1 presents the resulting fit from 2010Q1-2024Q2.

Our results are remarkably consistent with our earlier finding. Controlling for current wage growth does not change the character of the relationship, as quits and HPW continue to outperform other measures significantly. Throughout the sample, they are among the strongest indicators, but they completely separate from the pack after 2020 and remain the best predictors of future wage growth.

E Data Preparation and Construction of the HPW Index

In this section, we provide further details on the data preparation and on the construction of the HPW Index.

First, we construct the time series of the quits rate. We obtain the historical quarterly quits rate from Davis et al. (2012) and save the data between 1990q2 and 2010q2 as quitsDFH. We translate the quits into an average monthly quits rate by quarter by dividing the quits by 3. We also obtain the current quits rate of total private workers from JOLTS for 2001Q1 to today, available from FRED as JTS1000QUR. We generate a new series of quits as quitsDFH between 1990q2 and 2000q4, use the average of the FRED quits rate and quitsDFH from 2001q1 to 2010q2, and use the FRED quits rate from 2010q3 until today

In the next step, we construct the time series of wages. We download the historical, seasonally adjusted 3 month percent change of the ECI for wages and salaries of private workers for 1980-2005 (available at the SIC level) from the BLS (series ECS20002Q). For the recent data, we download the ECI for wages and salaries of private industry workers for 2001-today from FRED as ECIWAG. We then compute the quarterly change in the ECI index as (ECI – l.ECI) / l.ECI, where "l" denotes the lag operator. We merge the current and the historical series of 3-month ECI changes together and use the historical data for 1980-2001q1, the simple average of the current ECI and the historical ECI for 2001q2 to 2005q4, and the current ECI from 2006q1 onwards

Next, we download via Haver Analytics the following monthly series: 1) JOLTS: job openings: total, SA (LJJTLA@USECON); 2) Civilians Unemployed for Less Than 5 Weeks (SA, Thous.) (LU0@USECON); 3) Civilians Unemployed for 5-14 Weeks (SA, Thous.) (LU5@USECON); 4) Civilians Unemployed for 15-26 Weeks (SA, Thous.) (LU15 @USECON); 5) Civilians Unemployed for 27 Weeks and Over (SA, Thous.) (LUT27@USECON); 6) Not in the Labor Force, Marginally Attached (SA, Thous.) (LHWSA@USECON); 7) Not in Labor Force : 16 yr + (SA, Thous.) (LH@USECON); 8) Civilian Employment: Sixteen Years & Over (SA, Thous.) (LE@USECON). We merge this data with the other series.

We construct the number of short-term unemployed as the sum of unemployed less than 5 weeks, 5-14 weeks, and 15-26 weeks. We define workers out of the labor force that do not want a job as those that are not marginally attached by subtracting LHWSA@USECON from LH@USECON. We then define the short-term unemployed as U_s, long-term unemployed (27 weeks and over) as U_l, non-employed that want a job (marginally attached workers) as N_{want}, workers out of the labor force that do not want a job as $N_{dontwant}$, and employed as E. We compute the number of effective searchers as $ES = U_s + 0.48 * U_l + 0.4 * N_{want} + 0.09 * N_{dontwant} + 0.07 * E$. We convert the monthly data to quarterly data by taking an average across the months of the quarter

Next, we construct the time series of vacancies. We download the historical vacancy data from

Regis Barnichon's website from 1951m1 to 2021m8, and convert the monthly data to quarterly by taking an average of V_hwi and V/LF across the months of the quarter. We generate a new series of vacancies as V_hwi between 1990q1 and 2000q3, use the average of the JOLTS vacancies and V_hwi from 2000q4 to 2021q3, and use JOLTS vacancies for 2021q4 until today. We compute vacancies over effective searchers as VES = vacancies / ES.

We keep the data between 1994Q1 and 2024Q2, and run a simple linear regression of the 3m ECI changes on VES and the quits rate. The non-standardized HPW index is HPW_nosd = beta1*VES + beta2*quits rate, where beta1 and beta2 are the estimated OLS coefficients from the previous step. We standardize the index by computing the mean and standard deviation of HPW_nosd and then compute HPW=(HPW_nosd- MEAN(HPW_nosd)) /SD(HPW_nosd).

To generate Figure 2, we generate the smoothed ECI from the 3m changes of the ECI as ECI_smoothed=(ECI + l.ECI + f.ECI)/3, where "l" is the lag operator and "f" is the forward one quarter operator. At the boundaries in 1994q1 and 2024q2, we can only use the lead quarter or the lag quarter, respectively, for the smoothing. We standardize the smoothed ECI as ECI_smoothed_std =(ECI_smoothed-MEAN(ECI_smoothed))/SD(ECI_smoothed).

F Additional Nonlinearity Analysis

In this section, we present additional details on our regressions analyzing nonlinearity in the wage Phillips curve. Panel (a) of Table A.11 presents the full results from running equation (12). We include Newey-West standard errors with four lags. The coefficient of interest is β_3: it captures whether there is a change in the slope of the relationship between tightness and wage growth. While for the unemployment rate the coefficient on the interaction term, β_3, is quantitatively large, it is not significant at conventional levels. The coefficients on β_3 is insignificant for the other tightness measures. There does appear to be a statistically significant level shift at the break point for V/ES; however, the slope of the line is similar to before. Thus, we do not detect a significant change in the relationship between labor market tightness and wage growth for any of the measures.

To assess the presence of nonlinearity along all values of X_t rather than at a specific break point, we re-run the regression with a squared term of the tightness measure:

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \epsilon_t, \tag{16}$$

and present the results in panel (b) of Table A.11. The coefficient on the squared term is insignificant in all specifications, indicating again that we cannot reject a linear relationship.

Table A.11: Nonlinearities in Wage Growth Regressions

(a) Regressions with Threshold				
	(1)	(2)	(3)	(4)
	Unemployment	HPW	Quits	V/ES
$\mathbb{I}(X_t > \gamma)$	0.289	-0.000	0.050	0.191***
	(0.253)	(0.083)	(0.081)	(0.049)
X_t	-0.472*	0.200***	0.171***	0.168***
	(0.270)	(0.017)	(0.015)	(0.027)
$\mathbb{I}(X_t > \gamma) \cdot X_t$	0.328	0.033	0.039	-0.032
	(0.269)	(0.051)	(0.066)	(0.034)
Observations	137	122	137	122
R-squared	0.355	0.603	0.564	0.568

(b) Regressions with Nonlinear Term				
	(1)	(2)	(3)	(4)
	Unemployment	HPW	Quits	V/ES
X_t	-0.177	0.214	0.205	0.211
	(0.035)	(0.010)	(0.013)	(0.024)
X_t^2	0.017	0.013	0.016	-0.012
	(0.014)	(0.007)	(0.009)	(0.013)
Observations	137	122	137	122
R-squared	0.350	0.605	0.558	0.521

Notes: results from regressions of 3-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. The top panel shows regressions with a threshold, where γ is set at the 25th percentile for unemployment and at the 75th percentile for all other variables. The bottom panel shows regressions with an additional squared term of the independent variable. The variable X_t used is denoted in the top row. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.