Wage Growth and Labor Market Tightness

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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. Among 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. 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. We develop a new composite indicator of labor market tightness that can be used by policymakers to predict wage pressures in real time.

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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, traditional 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: 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 into 2022. 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 non-employed 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 (2025). 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. In particular, we find that a vacancy ratio that counts employed workers as searchers performs better than ratios that do not, such as the widely used vacancy-to-unemployment ratio V/U—consistent with the model's predictions. 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. To construct V/ES, we measure effective searchers in two alternative ways. First, as in Abraham, Haltiwanger, and Rendell (2020) (AHR), we use micro data from the Current Population Survey (CPS) to define 22 types of job seekers and compute effective searchers as a weighted sum of the shares of these workers in the population, where the weights are the workers' job finding rates. This modelling is motivated by the observation that workers' transition rates into employment, a proxy for workers' search intensity, vary significantly across types of workers (e.g., Hall and Schulhofer-Wohl, 2018). As an alternative, we also consider a simpler measure of effective searchers proposed by Şahin (2020), which uses only five worker types and does not require CPS micro data.

We then 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:q4. 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 Non-Employment Index (NEI) by Hornstein et al. (2014), the Aggregate Hours Gap by Faberman et al. (2020), as well as other variables. Consistent with the theory, the quits rate and vacancies per effective searcher track wage growth the best out of all the variables tested. In univariate regressions, quits alone explain 55 percent of wage growth, while V/ES explains 53 percent when we define effective searchers as in AHR and 52 percent when we define effective searchers as in Şahin (2020). Together, the quits rate combined with either V/ES measure explains nearly two-thirds of wage growth since 1994 and nearly 80 percent since the onset of COVID in 2020:q2.

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 conduct panel regressions of wage growth on labor market tightness indicators at the industry level, using 10 broad sectors available from JOLTS. Since we do not have good measures of the number of workers out of the labor force at the industry level, we define effective searchers using only the employed and unemployed, where we obtain the relative search intensities from Bloesch, Lee, and Weber (2025). 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, using V/ES yields the highest R-squared. Moreover, V/ES is the only indicator that remains statistically significant (other than the separation rate) when combined with quits.

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. Combining the two measures adds useful information about the state of the labor market because the two indicators capture related but distinct mechanisms of labor market dynamics: the quits rate is more a measure of labor market "churn" or reallocation, while V/ES is more directly a measure of tightness. Since the AHR and the Şahin measure of V/ES produce nearly identical results, we use the simpler Şahin measure for our baseline HPW Index since it does not rely on CPS micro data. We show that the HPW 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 estimate wage regressions over the entire sample period.

While the in-sample performance of our tightness measures is instructive, policymakers are particularly concerned with out-of-sample predictions. We therefore 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 2004:q1. 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. These measures are 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 the vacancy-based tightness measures V/U and V/ES has steadily deteriorated since 2015. This deterioration could be due 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.

In the final part of the paper, we extend the analysis to *price* inflation and perform a similar in-sample horse race and out-of-sample predictions for the core Consumer Price Index (CPI). While this analysis goes beyond our simple model of wage inflation, it is interesting to see whether our tightness measures can also predict price inflation. We find that both in sample and out of sample, our measures of vacancies per effective searcher, the quits rate, and the HPW index are the best predictors of price inflation among the tightness measures. Thus, our insights carry over to price inflation as well.

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; Bernanke and Blanchard, 2025). Our work is closely related to Galí (2011) and Bloesch, Lee, and Weber (2025) 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 (2025) 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 closely related measures from their model, quits and vacancies per effective searcher, 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 focusing primarily on U.S. *wage* inflation, but show that our insights also carry over to price 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., 2025), 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. 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 (2025) 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).

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. 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, and Section 6 examines the relationship between tightness and price inflation. Finally, Section 7 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 (2025), 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 (2025) 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 E_{jt} in period t decreases due to worker separations and increases due to recruiting, according to

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

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

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

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}, and vacancies V_{jt} to solve

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

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, $\mathcal{S}_t = \lambda_{EE}E_{t-1} + U_{t-1}$, where E_{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 $\lambda_{EE} < 1$.

Using the first-order conditions of the firm's problem (2) for vacancies and wages, Bloesch, Lee, and Weber (2025) 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

[2]In one specification of the model, Bloesch, Lee, and Weber (2025) 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.

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 must incorporate all active searchers, $\theta \equiv V/\mathcal{S}$. 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 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 (2025) find that $\beta_U \approx 0$ both in the calibrated model and in reduced-form, bivariate OLS regressions based on equation (3) estimated in 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, so the slope can be consistently estimated. We return to this issue in Section 6, when we estimate the relationship between tightness and price inflation. 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 (2025) 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. Note Bloesch, Lee, and Weber (2025) show that the role of unemployment is also relatively small in this formulation of the wage Phillips curve.

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.

2.2 Alternative Measures of Tightness

While the theory 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 a proxy for $V/\mathcal{S}$ perform best in predicting wage inflation, consistent with the theory outlined above. We select the alternative measures of labor market tightness to provide comprehensive coverage of the major theoretical and empirical approaches that have been prominent in both academic research and policy discussions. We include classic measures (unemployment, V/U) in addition to broader measures that have been more recently informed by empirical and theoretical literature on labor markets. Appendix A contains further documentation on each measure of tightness we consider in the paper.

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

Another standard 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).[3] 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. (2025) 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. A related 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

[3]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.

measure of labor market slack than the unemployment rate. Wage growth should be high when vacancies are plentiful relative to the number of unemployed.

Several papers have sought to broaden the concept of labor market slack beyond the unemployed. Hornstein, Kudlyak, and Lange (2014) develop a Non-Employment Index (*NEI index*), which is a weighted average of the population shares of different subgroups of unemployed and out of the labor force workers, where the weights are equal to the employment transition rate of each group. Faberman, Mueller, Şahin, and Topa (2020) measure the difference between desired and actual hours worked for different population groups, including employed workers and individuals out of the labor force, and aggregate these differences to an *Aggregate Hours Gap*. When this gap is large, wage growth is slower. Hall and Schulhofer-Wohl (2018) consider the vacancies-to-hires ratio as a measure of labor market tightness. When this ratio is high, it suggests that firms have a hard time attracting job seekers—which can include on-the-job searchers—to fill open positions, which may lead them to raise wages.

An alternative approach to measuring labor market slack is to consider workers' transition rates directly, such as 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. 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 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.

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. 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.

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.[4] 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.[5] 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. In Section 3.1, we describe our data and construct a proxy of searchers $\mathcal{S}$. In Section 3.2, we run a "horse race" to examine which of the tightness measures track wage inflation best. In Section 3.3, we run similar regressions at the industry level. Appendix B.1 plots the time series of several key tightness measures against wage growth and shows that they are correlated.

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

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

3.1 Data

Our analysis uses quarterly U.S. data for the period 1990:q2-2024:q4, 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., Bernanke and Blanchard (2025).[6] We compute the 3-month percent 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.

To construct the vacancies per searcher measure, $V/\mathcal{S}$, we need to take a stand on $\mathcal{S}$, the workers that are searching for jobs and their search intensity. The simple model introduced above assumes that only employed and unemployed workers search for jobs, and that within each group search intensity is homogeneous. However, individuals not in the labor force are also important job seekers, since the number of individuals out of the labor force that become employed in a given month exceeds the number of individuals that find a job from unemployment (Hornstein et al., 2014). Moreover, transitions to employment vary across different types of workers. For example, non-employed individuals that report wanting a job are significantly more likely to find employment than those that do not report wanting a job (Hornstein et al., 2014; Hall and Schulhofer-Wohl, 2018), and workers that were recently laid off have different job-finding rates from workers that were not (Katz and Meyer, 1990; Fujita and Moscarini, 2017).

To take into account this heterogeneity in transition rates into a new job, Abraham, Haltiwanger, and Rendell (2020) compute a measure of *effective* searchers. They define effective searchers as a weighted average of the population shares of 22 groups of workers, where the weights are given by

[6] 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.

the job finding rates of each group relative to the job finding rate of the recently temporarily laid off. The job finding rates are taken in a fixed base year, either 2006 or 2010. The worker groups include two groups for the employed, based on whether the worker is involuntarily part-time or not, 13 groups of unemployed workers, classified by the duration of unemployment and whether the worker was laid off or not, and seven groups of individuals out of the labor force, distinguished by whether the individuals want a job or not and by the individuals' current status (e.g., in school, retired, disabled). This classification builds on earlier work by Hall and Schulhofer-Wohl (2018), who measure job finding rates for slightly more aggregated 16 worker groups. Abraham, Haltiwanger, and Rendell (2020) show that their measure of effective searchers is substantially less volatile than unemployment, and produces a more stable Beveridge curve for the period 1994-2019 when used instead of the unemployment rate.

We follow Abraham, Haltiwanger, and Rendell (2020) and compute effective searchers from the CPS micro data between 1994 and 2024 as

$$\text{ES-AHR}_t = \sum_i f_i \cdot x_{it}, \tag{5}$$

where i indexes the 22 worker groups, x_{it} is the population share of worker group i in month t in the CPS, and f_i is group i's job finding rate in 2006 relative to the temporarily laid off, as in the original paper. We consider V/ES-AHR to be the empirically appropriate measure of labor market tightness. Details on the construction of ES-AHR and the definition of the worker groups are in Appendix A.1. We show in Appendix C that the results are robust to weighting the population shares using job finding rates from 1999 or 2013 as well.

While the ES-AHR$_t$ measure captures variations in the job finding rate across detailed groups, computation requires the use of the CPS micro data. Şahin (2020) shows that using a few broad labor market states captures almost all of the variation in effective searchers, and does not require the micro data. She computes effective searchers as:

$$\text{ES-S}_t = f_s U_t^s + f_l U_t^l + f_{want} N_t^{\text{want}} + f_N N_t^{\text{do not want}} + f_E E_t, \tag{6}$$

where U_t^s is the share of short-term unemployed individuals in the population 16 years and older, i.e., those that are unemployed less than 27 weeks, U_t^l is the share of individuals unemployed for at least 27 weeks, N_t^{want} is the share of workers not in the labor force that want to work, $N_t^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and E_t is the share of employed workers. The weights f_i are the job finding rates in Abraham, Haltiwanger, and Rendell (2020) aggregated to the broader worker groups. Şahin (2020) sets $f_s = 1$, $f_l = 0.48$, $f_{\text{want}} = 0.4$, $f_N = 0.09$, and $f_E = 0.07$. We replicate this measure using employment, unemployment, and workers not in the labor force from the CPS. Details are in Appendix A.2.[7]

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 obtain the NEI from Hornstein, Kudlyak, and Lange (2014), and the Aggregate Hours Gap from Faberman, Mueller, Şahin, and Topa (2020). We provide further details in Appendix A.2.

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

[7] In Appendix C, we experiment with different versions of the effective searchers weights for our main regression results.

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.

3.2 A "Horse Race" of Tightness Measures

We run OLS regressions of wage inflation on the tightness measures individually and jointly, following empirical work since at least Phillips (1958). We expect unemployment, continuing claims, and measures of labor market slack (NEI, Aggregate Hours Gap) to be negatively correlated with wage growth; higher slack predicts lower wage pressures. Conversely, measures of labor market tightness, including V/U, the job finding rate, the quits rate, and survey measures of hiring difficulty, should correlate positively with wage growth. The separation rate presents an ambiguous case, as it combines voluntary quits (indicating worker confidence) with involuntary layoffs (indicating labor market weakness). 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 percentage change in wage growth associated with a one standard deviation increase in each independent variable. Our regressions take the form

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

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 above, 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.

Table 1 reports results of estimating equation (7) separately with each of the various tightness measures. We report the estimated standardized coefficient and Newey-West standard errors with four lags, but note that some of the right-hand side variables are persistent. We also report model fit as measured by the R-squared. Appendix C Table A.1 reports standard regression tables underlying these results. The tightness measures are ranked by their ability to fit U.S. wage data since 1990. Consistent with the model, while the unemployment rate is negatively correlated with wage growth, our two measures V/ES-AHR and V/ES-S and the quits rate are positively correlated with wage growth. Also consistent with the model, quits, V/ES-AHR, and V/ES-S 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 1.7 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-AHR (by 0.02), V/ES-S (by 0.08), or quits (by 0.37) is associated with an increase in wage growth of 0.20 percentage points. The very similar fit of V/ES-AHR and V/ES-S indicates that the simpler tightness measure using effective searchers as defined by Şahin is a good approximation of the AHR-based measure, which tracks wage growth only marginally better. Both V/ES-AHR and V/ES-S perform better than the standard labor market tightness measure including only unemployed workers, V/U. The R-squared in the regressions involving V/ES-AHR, V/ES-S, and quits is greater than 0.5, substantially higher than the fit for V/U (0.41) and for unemployment (0.34). The aggregate hours gap also fits wage growth relatively well, coming fourth in our exercise.

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:

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t \tag{8}$$

where X_t is the standardized tightness measure in Table 1 above, and Q_t is the standardized quits

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

Measure X_t	**Coefficient on** X_t	**s.e.**	R^2
Quits Rate	0.20	(0.02)	0.55
V/ES-AHR	0.20	(0.02)	0.53
V/ES-S	0.20	(0.02)	0.52
Aggregate Hours Gap	-0.19	(0.02)	0.47
Jobs-Workers Gap	0.18	(0.02)	0.44
V/U	0.17	(0.02)	0.41
NFIB Difficulty Hiring	0.17	(0.03)	0.41
CB Jobs Availability	0.17	(0.03)	0.40
Vacancy/Hire	0.17	(0.03)	0.40
Non-Employment Index	-0.17	(0.03)	0.38
Job Finding Rate	0.16	(0.02)	0.37
Unemployment	-0.16	(0.02)	0.34
Acceptance Rate	-0.15	(0.03)	0.30
Hires Rate	0.12	(0.03)	0.20
Continuing Claims	-0.12	(0.04)	0.19
Separation Rate	-0.02	(0.04)	0.00

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, "s.e." reports the Newey-West standard errors with four lags, and we report the R-squared value from the simple univariate time-series regression (7): $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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 C Table A.1.

rate. Table 2 presents a set of coefficients on bivariate regressions that include quits alongside the other variables X_t. We present both coefficients, Newey-West standard errors, and the R-squared (fit). Appendix C Table A.2 contains the associated standard regression tables.

We find that the combination of the quits rate and either measure of V/ES fits wage growth best, and quits consistently has the highest coefficient value associated with it.[8] 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 many of the other measures of tightness we consider, with the important

[8] Appendix B contains additional figures showing the time series of the central labor market indicators and wage growth, in addition to the correlation between quits and V/ES; they are strongly, but not perfectly, correlated.

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

Measure X_t	**Coefficient on** X_t	**s.e.**	**Quits Coefficient**	**s.e.**	R^2
V/ES-AHR	0.09	(0.03)	0.13	(0.02)	0.61
V/ES-S	0.08	(0.03)	0.13	(0.03)	0.60
Acceptance Rate	0.03	(0.02)	0.22	(0.02)	0.60
Aggregate Hours Gap	-0.06	(0.03)	0.15	(0.03)	0.59
Non-Employment Index	-0.03	(0.02)	0.17	(0.03)	0.58
NFIB Difficulty Hiring	0.02	(0.04)	0.18	(0.03)	0.57
Vacancy/Hire	0.05	(0.03)	0.16	(0.02)	0.56
V/U	0.05	(0.03)	0.16	(0.02)	0.56
Job Finding Rate	0.02	(0.03)	0.18	(0.03)	0.55
Jobs-Workers Gap	0.03	(0.04)	0.18	(0.04)	0.55
Separation Rate	0.01	(0.02)	0.20	(0.02)	0.55
Hires Rate	-0.01	(0.03)	0.21	(0.02)	0.55
Continuing Claims	-0.00	(0.02)	0.20	(0.02)	0.55
CB Jobs Availability	0.00	(0.04)	0.20	(0.04)	0.55
Unemployment	0.00	(0.03)	0.20	(0.03)	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 (8): $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$. "Quits Coefficient" reports the coefficient on quits, β_2, "s.e." reports the Newey-West standard errors with four lags, and we report the R-squared value. All measures of tightness remain ordered by their R^2. Estimates use data from 1990:q2–2024:q4, or shorter horizons when less data are available. Definitions of all measures can be found in Appendix A; underlying OLS regressions can be found in Appendix C Table A.2.

exception of the V/ES measures and the aggregate hours gap. Once we incorporate quits, most 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 model's 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).

Appendix C provides several additional robustness checks of our findings. First, we consider alternative definitions of V/ES: we use the 16 worker groups by Hall and Schulhofer-Wohl (2018) to compute effective searchers as an alternative to Abraham, Haltiwanger, and Rendell (2020), compute effective searchers using the job finding rates in 1999 and 2013 instead of the one from 2006, and use the measure of recruiting intensity by Davis, Faberman, and Haltiwanger (2013) as an alternative measure of vacancies in the numerator of V/ES (Table A.3 and A.4). Results from using different measures of effective searchers are very similar, but using recruiting intensity instead of vacancies for V/ES lowers the fit of wage growth. Second, we re-run the regressions where we additionally include a linear time trend on the right-hand side (Table A.5 and A.6). Alternatively, we detrend all tightness variables by regressing them on a linear time trend and use the residual tightness measure in our regressions (Table A.7 and A.8). We find that in the univariate regressions our two measures of vacancies per effective searcher now have the highest fit, followed by V/U and the quits rate. The good performance of the vacancy-based measures once we detrend them is consistent with vacancies following an upward trend over our sample period. In the bivariate regressions the combination of vacancies per effective searcher and the quits rate still performs best, and substantially better than the combination of quits rate and V/U.

We next restrict the analysis to the pre-COVID periods 1990:q2-2014:q4 and 1990:q2-2019:q4 (Table A.9 and A.10). We find that in the period from 1990 to 2014, the two measures of effective searchers and the quits rate perform best; only the job-finding rate has a higher fit of wage growth over this period. Once we add the five years to 2019 to the sample, the quits rate still performs well, but the vacancies per searcher measures have a lower fit, although still above the traditional V/U measure and the unemployment rate. The relatively weaker performance of the vacancies per effective searcher measures once we add the five years from 2015 to 2019 is consistent with their relatively lower out-of-sample forecasting performance during that period as well, a point we return to in Section 4.3. The vacancies per effective searcher measures and the quits rate perform substantially better than all other measures from 2020 onwards, making them the measures with the highest fit over the full sample period.

Finally, we run the wage growth regressions with 12-month changes rather than 3-month changes to examine the fit over longer horizons (Table A.11). The quits rate and our two measures of vacancies per effective searcher remain the best predictors of 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 (7) at the industry-level:

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

where i indexes the industry, t indexes the quarter, Π_{it}^{w} 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 10 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:q4 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 non-employed workers by industry, we are not able to compute measures of 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 (2025). The NFIB

[9]The 10 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.

Difficulty Hiring measure, CB Jobs Availability, Acceptance Rate, Aggregate Hours Gap, NEI, 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 3 in the same way as above and show the standardized regression coefficient and the within R-Squared (fit) for each variable. We also include Driscoll-Kraay standard errors with one lag, which account for cross-sectional correlation and correlation in the time series. The detailed regression results are in Appendix D.

Table 3: Industry-Level Wage Growth Regressions

Measure X_t	**Coefficient on** X_t	**s.e.**	R^2
Quits Rate	0.23	(0.06)	0.020
V/ES	0.13	(0.04)	0.010
Hires Rate	0.11	(0.06)	0.005
Jobs-Workers Gap	0.08	(0.04)	0.004
Unemployment	-0.06	(0.03)	0.003
Separation Rate	-0.05	(0.03)	0.002
Vacancy/Hire	0.03	(0.04)	0.001
V/U	0.01	(0.03)	0.000
Job Finding Rate	0.00	(0.03)	0.000

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, "s.e." reports the Driscoll-Kraay standard error with one lag, and we report 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 (R^2). Estimates use data from 2001:q1–2024:q4. 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 are in Appendix D, Table A.15. Appendix Table A.17 presents the results without time fixed effects.

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 also run bivariate regressions, as before, 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 4 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.

Table 4: Bivariate Industry-Level Regressions: Quits and Others

Measure X_t	**Coefficient on** X_t	**s.e.**	**Quits Coefficient**	**s.e.**	R^2
V/ES	0.08	(0.04)	0.20	(0.05)	0.024
Separation Rate	-0.06	(0.03)	0.23	(0.06)	0.023
Vacancy/Hire	0.06	(0.04)	0.24	(0.06)	0.022
Jobs-Workers Gap	0.04	(0.03)	0.22	(0.06)	0.022
Unemployment	-0.04	(0.03)	0.22	(0.06)	0.021
V/U	0.02	(0.03)	0.23	(0.06)	0.021
Job Finding Rate	-0.00	(0.03)	0.23	(0.06)	0.020
Hires Rate	0.01	(0.04)	0.23	(0.05)	0.020

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, "s.e." reports the Driscoll-Kraay standard error with one lag, and we report the within R-squared value from the panel regression (9) with the quits rate additionally included: $\Pi^w_{it} = \beta_1 X_{it} + \beta_2 Q_{it} + \gamma_i + \rho_t + \epsilon_{it}$. All measures of tightness are ordered by their fit. Estimates use data from 2001:q1–2024:q4. 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 D, Table A.16. Appendix Table A.18 presents the results without time fixed effects.

While recent work has estimated price Phillips curves with variation across states (e.g., Hazell et al., 2022), running similar regressions for wages at the state-level is subject to significant caveats. First, our left-hand side variable, the ECI, is not available at the state level. To run state-level regressions, we would therefore have to rely on noisier measures of wage growth, unadjusted for occupation and industry characteristics, such as from the Quarterly Census of Employment and Wages. Second, the BLS does not directly measure state-level variables in JOLTS but imputes them using statistical models. This is because the sample size of the JOLTS survey is too small to directly support state level estimates, raising additional concerns about noise and measurement error.[10] We therefore do not include state-level results.

[10]JOLTS covers only about 21,000 establishments nationwide. For more details, see https://www.bls.gov/jlt/jlt_statedata_methodology.htm. According to the BLS: "JOLTS data are somewhat volatile at the national and regional levels due to the small sample size which in turn results in volatile state estimates."

4 Applications: An Index and Forecasting

The previous analysis has highlighted that the quits rate and measures of vacancies per searcher are most strongly correlated with wage inflation amongst a broad range of widely-used labor market tightness measures in both aggregate data and industry-level panel data. Building on this insight, in Section 4.1 we develop a parsimonious index of labor market tightness that combines the quits rate and vacancies per effective searcher. We then perform forecasting regressions in Section 4.2 and out-of-sample predictions of wage growth in Section 4.3 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.

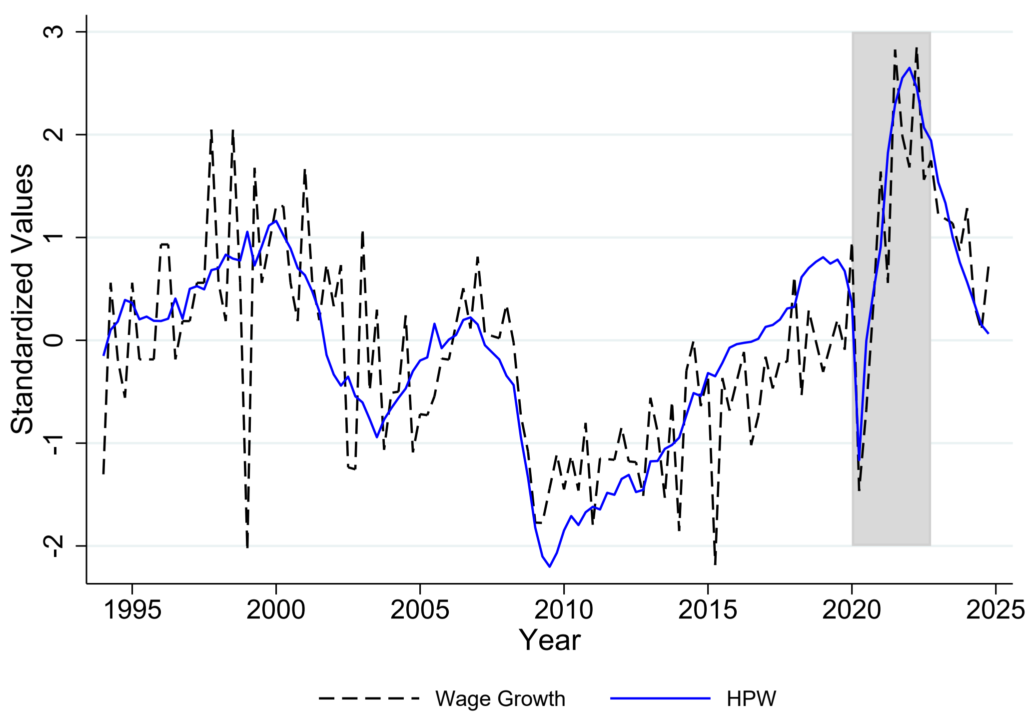
4.1 An Index for Wage Growth

We generate a parsimonious labor market tightness index that uses as inputs quits and V/ES. This index is a useful visual summary of our findings. It is motivated by the following: (1) the model predicts that either quits or vacancies per searcher is nearly a sufficient statistic for wage growth; (2) these two indicators track wage growth best among a variety of indicators, as seen in Table 1; (3) both indicators capture related but distinct mechanisms driving labor market dynamics: on the one hand, the quits rate is more a measure of labor market "churn" or worker reallocation. On the other hand, V/ES is more directly a measure of tightness. Combining the two measures adds useful information compared to using the measures separately. For example, the same V/ES ratio could describe a labor market with high vacancies and high overall churn, or a labor market with low levels of both. The combination of both measures allows us to infer the state of the labor market more accurately.

To construct the index, we take a weighted average across the quits rate and vacancies over effective searchers, using as weights the fitted values from the regression underlying the second 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*. We construct our index using V/ES-S as a measure of vacancies per searcher since it performs nearly as well as V/ES-AHR in all analyses above, and does not require the CPS micro data, which is only released with a delay of one week. It is therefore easy to compute and gives policymakers a tool to track wage growth in real time. As for all other variables, we normalize the HPW index to have mean zero and standard deviation of one. Appendix A.3 provides details on the index construction.

Figure 1 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 0.78. 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.

Figure 1: HPW Index vs. 3-Month Wage Growth



Notes: The HPW Index is computed as a weighted average of the quits rate and V/ES-S, where the weights are obtained from the second 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.

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 alternative 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. 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 (7) 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 5 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, together with Newey-West standard errors. Detailed regression tables can be found in Appendix C Tables A.12, A.13, and A.14. 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 0.21, 0.20, and 0.18 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 0.37) is associated with wage growth of 0.20, 0.19, and 0.18 percentage points respectively for next one, two, and four quarters. The V/ES-AHR

Table 5: Future Wage Growth Regressions

	1Q Ahead			2Q Ahead			4Q Ahead		
Variable	Coef.	s.e.	Fit	Coef.	s.e.	Fit	Coef.	s.e.	Fit
HPW	0.21	(0.01)	0.61	0.20	(0.01)	0.55	0.18	(0.01)	0.45
Quits Rate	0.20	(0.02)	0.57	0.19	(0.02)	0.52	0.18	(0.01)	0.45
V/ES-AHR	0.20	(0.02)	0.51	0.18	(0.02)	0.44	0.16	(0.02)	0.35
V/ES-S	0.19	(0.02)	0.50	0.18	(0.02)	0.44	0.17	(0.02)	0.35
CB Jobs Availability	0.17	(0.03)	0.40	0.16	(0.03)	0.36	0.15	(0.02)	0.33
NFIB Difficulty Hiring	0.17	(0.03)	0.40	0.17	(0.03)	0.40	0.16	(0.02)	0.34
Jobs-Workers Gap	0.17	(0.02)	0.40	0.15	(0.03)	0.33	0.14	(0.02)	0.26
Vacancy/Hire	0.17	(0.03)	0.39	0.17	(0.03)	0.38	0.16	(0.02)	0.35
V/U	0.16	(0.02)	0.38	0.15	(0.03)	0.32	0.13	(0.02)	0.25
Agg. Hours Gap	-0.17	(0.03)	0.37	-0.15	(0.04)	0.28	-0.12	(0.04)	0.17
Acceptance Rate	-0.16	(0.02)	0.31	-0.15	(0.02)	0.30	-0.15	(0.02)	0.27
Non-Employment Index	-0.15	(0.04)	0.28	-0.12	(0.05)	0.19	-0.10	(0.05)	0.12
Job Finding Rate	0.14	(0.02)	0.28	0.12	(0.03)	0.22	0.11	(0.03)	0.16
Unemployment	-0.14	(0.03)	0.27	-0.12	(0.04)	0.19	-0.10	(0.04)	0.14
Hires Rate	0.13	(0.03)	0.22	0.13	(0.02)	0.24	0.13	(0.02)	0.24
Continuing Claims	-0.09	(0.05)	0.12	-0.07	(0.06)	0.06	-0.04	(0.07)	0.02
Separation Rate	-0.02	(0.03)	0.01	-0.01	(0.03)	0.00	-0.01	(0.03)	0.00

Notes: "Coefficient" reports the increase in wages (in percentage points) associated with a one-standard deviation increase in each indicator, "s.e." are Newey-West standard errors, and we report the R-squared value from the simple univariate time-series regression (10): $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t$, 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:q4, 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 C Tables A.12, A.13, and A.14.

measure is the third-best predictor over all horizons, followed by V/ES-S. All other measures of labor market tightness have lower fit and lower standardized coefficients in absolute value.

As a robustness check, we analyze whether the same pattern holds when we include the current three-month wage growth as an additional control in regression (10) for the three-month horizon. Results in Table A.19 in Appendix E are very similar to the baseline.

4.3 Out-of-Sample Forecasts

While the previous section has shown that the HPW Index, the quits rate, measures of vacancies per searcher predict wage growth well in sample, a more stringent test of these metrics is whether they can forecast wage growth in the next period with *only the available data at a given point in time*, i.e., out of sample. We 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:

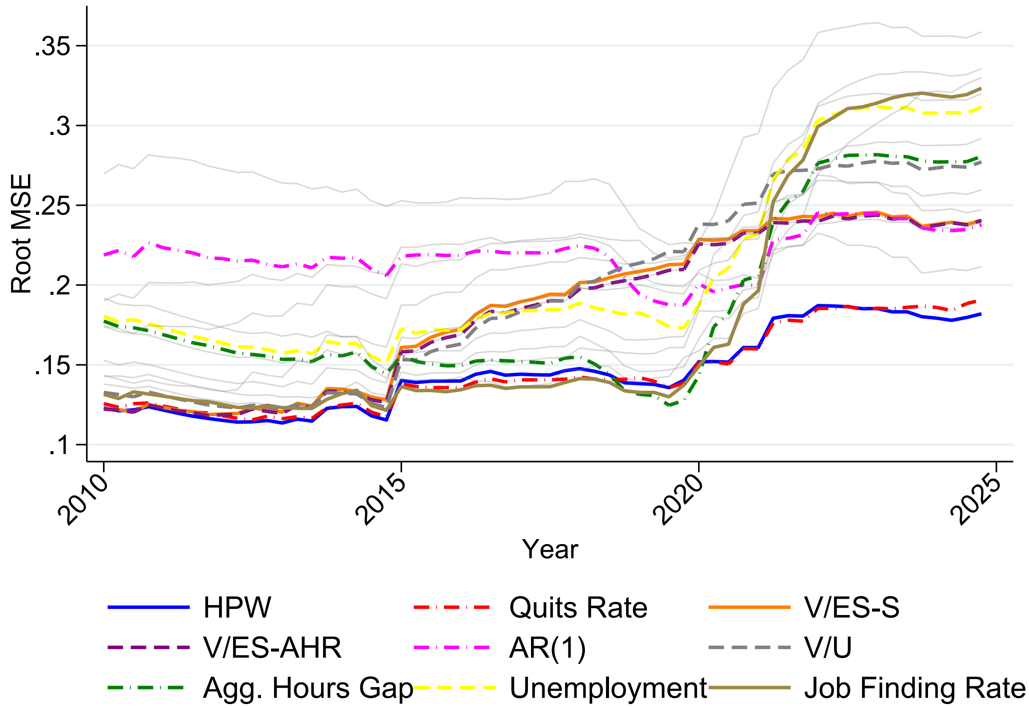
$$\Pi^w_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_t \text{ for } t < T. \tag{11}$$

In contrast to before, we estimate this regression using only data from the start of our sample to quarter T, and then use the estimated coefficients to predict wage growth in $T + 1$. Importantly, in each quarter, we *re-compute the HPW index* with new weights obtained by running the bivariate regression (8) of wage growth on quits and V/ES-S using only data available up to that point in time. Thus, as opposed to Table 2, which takes as inputs uniform weights, we obtain a new vintage of the HPW for each time horizon T. This procedure ensures our out-of-sample forecasts use only information that is available to policymakers in real-time. The resulting time-varying weights further allow the index to adapt to potential changes in the relative importance of quits versus vacancy-based measures over the sample period.

The regression delivers a predicted value $\hat{\Pi}^w_{T+1}$. Given that our first data point for the HPW Index is in 1994:q1, we start with 40 quarters of data to run our first regression for T =2003:q4 (Estimation period: 1994:q1–2003:q4), predicting out of sample the wage growth in 2004:q1. We then roll our methodology forward to T =2004:q1, estimate the model for 1994:q1–2004:q1, and predict the wage growth for 2004:q2. We continue producing forecasts up until the last quarter 2024:q4. 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 the window that ends in 2010:q1. For the first four years, we take a smaller window due to data limitations as the out-of-sample forecast starts in 2004:q1.

We plot the RMSE associated with the rolling window ending in quarter t for each of our tightness measures in Figure 2. As a benchmark, we compute the RMSE also for a simple AR(1)

Figure 2: 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 2004:q1 against the HPW index and other labor market indicators. X-axis denotes the end of the 40-quarter rolling window. For ease of reading, we only add color to selected series. Note that quits and HPW are the only two measures to consistently outperform the AR(1); the grey line that lies between HPW, Quits and the AR(1) post-COVID is the Vacancy/Hire ratio, which does not consistently beat the AR(1) in the pre-COVID period.

model for wage inflation (pink 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, as do the V/ES measures to a lesser extent. 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 the work by Mongey and Horwich (2023) finding that the relationship between vacancies and other labor market variables appears to have shifted over time. Among all our indicators, only quits and HPW consistently outperform the simple AR(1) model (Vacancy/Hire outperforms the AR(1) only in recent years).

In Appendix E we perform several robustness exercises. First, the good performance of the

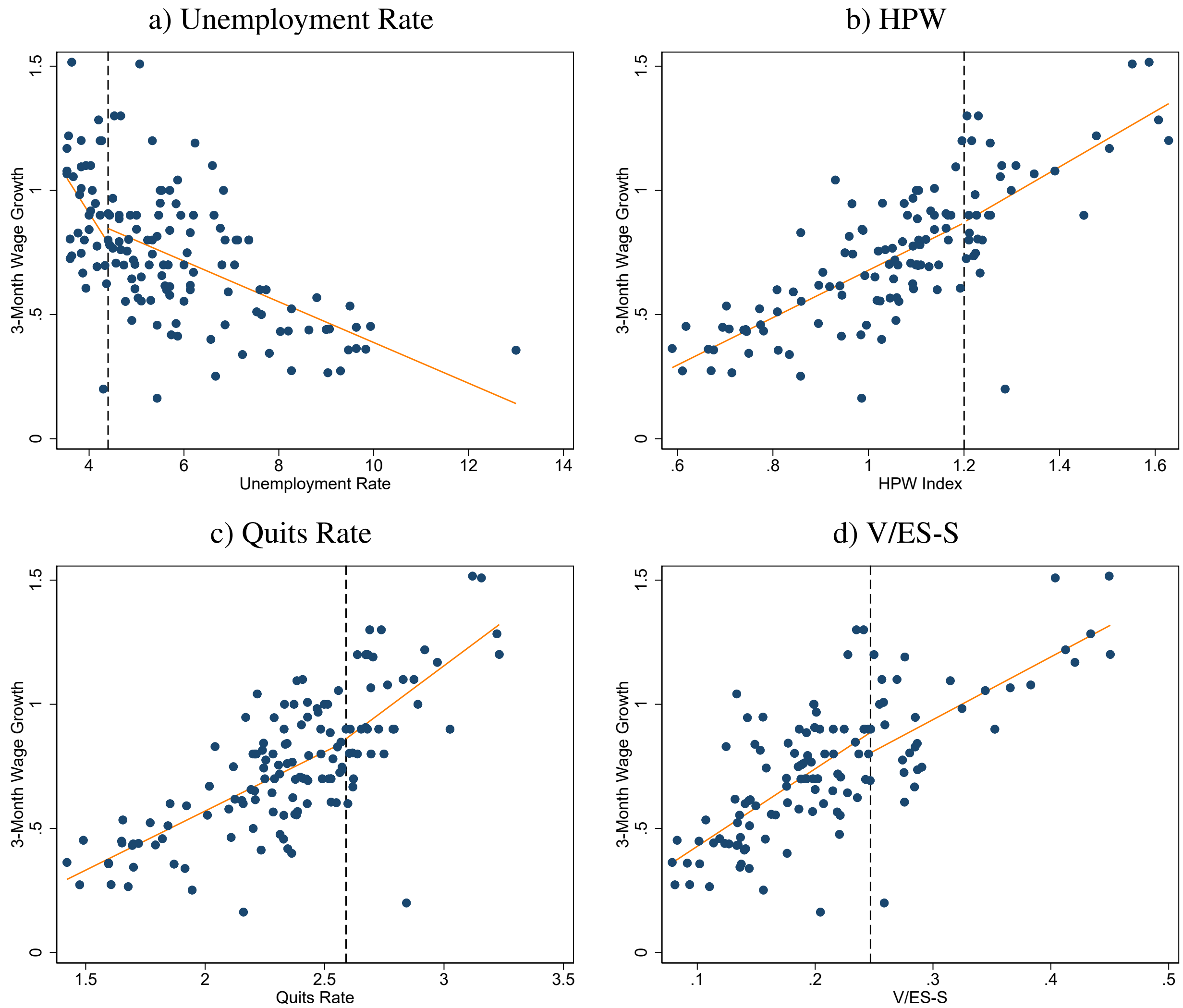
AR(1) model motivates us to examine how robust our results are to the inclusion of lagged wage growth in our regressions, in addition to our labor market tightness measures. We find that allowing for current wage growth to directly affect future wage growth in the regressions underlying the forecasting regressions in Figure 2 does not alter the results (Figure A.3). Second, we show that including a linear time trend significantly improves the performance of the V/ES measures in the post-COVID period (Figure A.4). When a linear trend is included, HPW, the quits rate, and the two V/ES measures perform best out of sample in the post-COVID period. Third, we compare the out-of-sample forecasting performance V/ES for different measures of vacancies and effective searchers (Figure A.5). We find that measures of V/ES that use recruiting intensity by Davis, Faberman, and Haltiwanger (2013) as a proxy for vacancies perform better out of sample in the pre-COVID period than measures that use the job openings from JOLTS. However, this ranking flips in the post-COVID period.

Overall, our 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 2. 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

Figure 3: Nonlinearity in the Tightness - Wage Growth Relationship



Notes: Figures show scatterplots of 3-month wage changes from the ECI for the period 1990:q2-2024:q4 against the unemployment rate, the HPW index, the quits rate, and V/ES. Each dot indicates a quarterly observation. Dashed vertical lines denote the selected break point of the relationship, which is chosen as the 25th percentile of the values for unemployment and as the 75th percentile of the values for the HPW index, quits rate, and V/ES-S. Orange lines indicate the best linear fit to the left and to the right of the break point.

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. We focus here on V/ES-S but analyze V/ES-AHR among the other indicators in Appendix F.1.

Panel (a) of Figure 3 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 non-linearity, 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 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-S 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.[11]

We evaluate the presence of nonlinearities with respect to tightness more formally in Appendix F.1, where we re-run our baseline regression (7) but include a threshold term that allows for a change in the relationship between wage growth and the tightness measure when the labor market is tight. We also re-run the regression with squared tightness terms. We find the baseline (linear) regression has a very similar fit to these non-linear specifications for all variables, suggesting very little role for nonlinearities.

One caveat to our analysis is that it is based on the full time series variation, and is not relative to any potential trend movements in the underlying variables. In general, small movements in the unobserved trends of the tightness measures could affect our results. While we do not perform a comprehensive trend-cycle analysis, we show in Appendix F.1 that the results are similar when we detrend all tightness variables using a *linear* time trend. We also present in the appendix scatterplots for all other tightness variables. These figures illustrate that for some variables the wage-tightness relationship *is* nonlinear: for the NFIB Index of the Difficulty Hiring, the Conference Board jobs availability measure, the job-workers gap, the vacancies/hires ratio, the Non-Employment Index, and for continuing claims wage growth increases more strongly with tightness

[11] We note that a linear relationship between quits or vacancies per searcher and wage growth can be perfectly consistent with a *nonlinear* relationship between unemployment and wage growth if there is a nonlinear relationship between tightness and unemployment. Indeed, standard matching models imply such a relationship between tightness and unemployment in steady state. Appendix F.2 provides further details.

when the labor market is hot than when it is cool.

Overall, this section shows that there is little evidence of nonlinearities in the wage-tightness relationship for our main measures. However, the relationship is nonlinear for some other variables.

6 Tightness and Consumer Prices

In this final section, we analyze whether quits and V/ES can also explain *price* inflation. The standard price Phillips curve relates price inflation to movements in marginal costs. If changes in marginal costs are well-approximated by changes in wages, we might expect that the labor market tightness measures also track movements in price inflation. However, this is not necessarily the case, as the pass through from wages into prices will generally vary for different shocks: for example, in the version of Bloesch et al. (2025) with sticky wages and flexible prices we considered in Section 2.1, transitory demand shocks will cause higher nominal wages and higher prices (through greater labor market tightness), but transitory supply shocks will cause *lower* nominal wages and higher prices (through *lower* labor market tightness).[12] Whether our measures of labor market tightness are good predictors of price inflation is therefore an empirical question.

To examine the relationship between price inflation and labor market tightness, we run quarterly regressions analogous to specification (7):

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

where Π_t^p is price inflation between quarter $t-1$ and quarter t and X_t is the tightness measure in quarter t. As before, we normalize all right-hand side variables to have mean zero and standard deviation of one, and thus regression coefficients indicate the percentage change in price inflation associated with a one standard deviation increase in each independent variable. We use the Core Consumer Price Index (CPI) as our measure of price inflation. This price series omits volatile

[12] See the supplementary online appendix to Bloesch et al. (2025) available on those authors' websites here for a simple AD-AS framework in which these results can be easily shown analytically.

Table 6: Consumer Price Inflation and the Labor Market Tightness Measures Ranked by Fit

Measure X_t	**Coefficient on** X_t	**s.e.**	R^2
V/ES-AHR	0.22	(0.04)	0.55
V/ES-S	0.22	(0.04)	0.54
HPW	0.21	(0.05)	0.48
Vacancy/Hire	0.18	(0.05)	0.34
Quits Rate	0.17	(0.05)	0.30
NFIB Difficulty Hiring	0.16	(0.05)	0.29
Aggregate Hours Gap	-0.16	(0.04)	0.28
V/U	0.16	(0.05)	0.26
Non-Employment Index	-0.15	(0.04)	0.24
Jobs-Workers Gap	0.15	(0.05)	0.22
Job Finding Rate	0.14	(0.04)	0.18
Unemployment	-0.11	(0.04)	0.12
Continuing Claims	-0.11	(0.04)	0.11
CB Jobs Availability	0.10	(0.06)	0.10
Acceptance Rate	-0.09	(0.04)	0.09
Hires Rate	0.09	(0.04)	0.08
Separation Rate	0.01	(0.08)	0.00

Notes: "Coefficient" reports the increase in core CPI (in percentage points) associated with a one-standard deviation increase in each indicator, "s.e." reports the Newey-West standard errors, and we report the R-squared value from the simple univariate time-series regression (12): $\Pi_t^p = \beta_0 + \beta_1 X_t + \epsilon_t$. All measures of tightness are ordered by their R^2. Estimates use data from 1990:q2–2024:q4, 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 G Table A.22.

energy and food prices from the consumer basket.

As discussed already in Section 2.1, compared to the wage analysis we have a greater potential for bias when we run this regression with prices. In the wage Phillips curve, shocks like TFP and monetary policy shocks affect wage inflation only through the tightness term. That is not the case in the price Phillips curve, where these shocks can affect price inflation independently beyond their effect through tightness, which causes omitted variable bias. In general, wage Phillips curves ought to have fewer issues with identification, as pointed out by, e.g., McLeay and Tenreyro (2020).

Table 6 shows the results from regression (12). We find that vacancies per effective searcher and the quits rate are also among the variables with the highest explanatory power for price inflation. In particular, vacancies per effective searchers tracks core CPI best, with a fit of 0.55 for V/ES-AHR and 0.54 for V/ES-S, and the quits rate is the fifth-best explanatory variable with a fit of 0.30. These measures are significantly better than traditional measures of tightness such as V/U or the unemployment rate. Our result is consistent with Barnichon and Shapiro (2024), who, focusing on price inflation, show that for the period 2005-2023 a measure of vacancies per effective searchers is one of the best predictors of core PCE. We complement their results by showing that the quits rate also tracks price inflation well and by analyzing a different set of labor market tightness variables.

In Appendix G, we perform bivariate regressions of CPI against the quits rate and one other tightness measure, as in specification (8), and find that including V/ES along with the quits rate generates the highest fit (Table A.23). We also find evidence of a nonlinear relationship between tightness and *price* inflation, consistent with, e.g., Benigno and Eggertsson (2024) (Figure A.9).

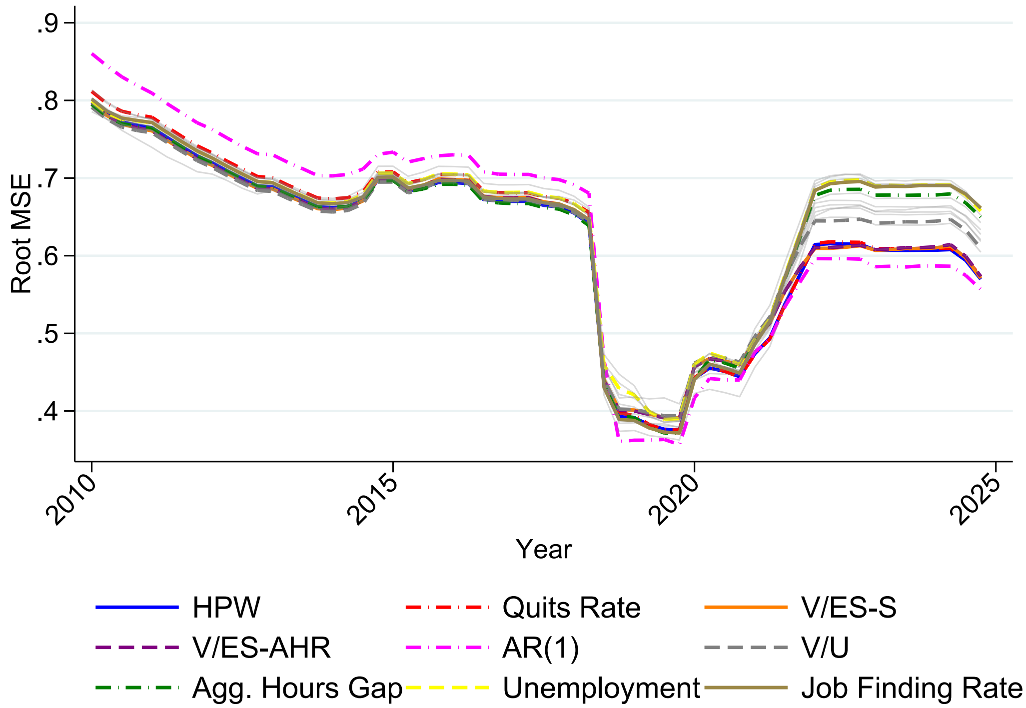
We next perform the out-of-sample analysis for consumer prices, as in Figure 2. As before, we compute the one-quarter ahead out-of-sample forecast of price inflation, and then plot the average RMSE associated with the 40-quarter rolling window of out-of-sample forecasts for each of our tightness measures. Figure 4 shows that in the first half of the sample period, the RMSE is very similar for all the measures. In the post-COVID period, however, the measures diverge, with the HPW, quits rate, and vacancies per effective searcher performing best. However, none of these measures beats a simple AR(1) process, in contrast to the findings for wage inflation. Thus, overall, vacancies per effective searcher and quits are also good predictors of price inflation.

7 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 non-employed 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 a simple measure of vacancies per searcher which does not require CPS micro data. This index

Figure 4: Forward Price Inflation on Different Measures, $RMSE$



Notes: Figure plots the RMSE over 40-quarter rolling windows from one-period ahead out-of-sample 3-month price changes from the CPI starting in 2004:q1 against the HPW index and other labor market indicators. x-axis denotes the end of the 40-quarter rolling window. For ease of reading, we only add color to selected series.

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 (2025). We find little evidence of any meaningful nonlinearity in the wage Phillips curve. In the final part of the paper, we show that the quits rate and measures of vacancies per searcher are also among the best predictors of *price* inflation.

Our results can help policymakers assess the state of the labor market and calibrate monetary policy. One question for future research is the coexistence of a nonlinear price Phillips curve with a linear wage Phillips curve. While broadly consistent with the fact that firms vary their pass-through of wage pressures into prices based on the state of the labor market (Amiti et al., 2024), we leave a formal rationalization of these findings for future work.

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Supplementary Materials (Not for Publication)

The Appendix provides more details on data sources and construction, expands on the specifications in the main text, and performs further robustness checks on the core messages. Appendix A provides a more detailed description of the construction of the measures of effective searchers, discusses each labor market indicator by its source, definition, and time period used in the paper, and describes the construction of the data. Appendix B provides some additional figures to illustrate time series variation in labor market tightness and the relationship between tightness and quits. Appendix C reports the detailed regression results from the main text and provides additional robustness analyses. Appendix D expands on industry-level regressions in the main text. Appendix E presents some additional robustness analysis for the forecasting regressions. Appendix F shows additional results from the nonlinearity analysis. Finally, Appendix G presents regression tables from the relationship between tightness and price inflation.

A Data Construction

In this section, we provide more detail on how we construct the labor market tightness indicators discussed in the main text and provide information on the sample period for which they are available. We describe the construction of the effective searchers measure in Section A.1, discuss the construction of the tightness measures in Section A.2, and report in detail the construction of the HPW Index to enable other researchers and interested readers to produce the measure in Section A.3.

A.1 Computing Effective Searchers from the CPS Micro Data

We construct two main measures of effective searchers. We compute the first measure, ES-AHR, following Abraham, Haltiwanger, and Rendell (2020) from the CPS micro data. Our second measure, ES-S, does not require access to the micro data. This section describes how we compute ES-AHR.

To construct ES-AHR, we use the CPS micro data for the period 1994:m1 - 2024:m12. We prepare the data following the process of Hall and Schulhofer-Wohl (2018). First, we use the method of Nekarda (2009) to match respondents across months. Next, we remove likely spurious transitions between unemployment and nonparticipation, and reweight the data to account for attrition from the survey. See Hall and Schulhofer-Wohl (2018) for details.

We then follow Abraham, Haltiwanger, and Rendell (2020) and define 22 labor market groups. For the unemployed, we define six groups for those unemployed for three weeks or less:

- Unemployed: Recently left job
- Unemployed: Recently permanently laid off
- Unemployed: Recently temporarily laid off
- Unemployed: Temporary job recently ended
- Unemployed: Recently newly entered
- Unemployed: Recently reentered

We similarly define six groups for those unemployed for 4 to 26 weeks:

- Unemployed: Left job months ago
- Unemployed: Permanently laid off months ago
- Unemployed: Temporarily laid off months ago
- Unemployed: Temporary job ended months ago
- Unemployed: Newly entered months ago
- Unemployed: Re-entered months ago

We define one group for the long-term unemployed:

- Unemployed: Long-term unemployed

We define three groups for workers out of the labor force that want a job, and four groups for those out of the labor force that do not want a job:

- Want job: Discouraged
- Want job: Looked last 12 months
- Want job: Other
- Not in labor force: In school
- Not in labor force: Retired
- Not in labor force: Disabled
- Not in labor force: Other

Finally, we create two labor force groups for employed workers:

- Employed: Involuntary part-time
- Employed: Not involuntary part-time

For each group i, we compute the population share x_{it} in each month t.

We compute each group's job finding rate f_i using the same two-step procedure as in Hall and Schulhofer-Wohl (2018) and Abraham, Haltiwanger, and Rendell (2020) to control for changing demographics. First, for each set of workers with characteristics x in each of the 22 worker groups we estimate a logit model according to

$$f_{jtx} = \frac{exp(\kappa_{jt} + x'\beta_j)}{1 + exp(\kappa_{jt} + x'\beta_j)}, \tag{13}$$

where f_{jtx} is the job finding rate of worker j in month t with characteristics x and the κ_{jt} are group-specific time effects. The characteristics x are six age groups, gender, marital status, four education groups, and more detailed unemployment duration group controls for all of the unemployed groups with 5-26 weeks of unemployment. Our analysis holds the demographic composition constant based on each group's characteristics in 2005-2007.

In the second step, we take the predicted monthly job finding rates from (13) for each cell defined by j, t, and x and aggregate these using the distribution within each worker group i across characteristics x in 2005-2007. This step yields monthly job finding rates for each worker group i in each month t for the period 1994:m1-2024:m12. In our baseline we then take an average over these job finding rates across the 12 months in 2006 for each group to obtain the fixed job finding rate in 2006, f_i, for each group. We test robustness to different years in Appendix C. We normalize the job finding rates so that the relative job finding rate of the recently temporarily laid off is $f_i = 1$. For employed workers, we use the job-to-job transition rate as the relevant job finding rate. We then obtain the measure of effective searchers, ES-AHR, from

$$\text{ES-AHR}_t = \sum_i f_i \cdot x_{it}. \tag{14}$$

We collapse the measure from the monthly to the quarterly level, taking a simple average across months.

A.2 Tightness Measures

In this section, we describe the construction of all tightness measures.

- **Unemployment rate**: Source: BLS. The unemployment rate (U-3) is defined as the number of unemployed individuals as a share of the labor force, where the labor force is restricted to people 16 years or older who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces. The number of unemployed and the size of the labor force are computed from the Current Population Survey (CPS). Availability: 1990:q2-2024:q4.

- **V/U**: Source: BLS, Barnichon (2010). This measure is defined as vacancies / number of unemployed. Vacancies are from JOLTS for 2001:q1-2024:q4 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1990:q2-2000:q4. Number of unemployed is the number of individuals aged 16 or older from the noninstitutional, civilian population reporting to be unemployed. Availability: 1990:q2-2024:q4.

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

- **V/ES-AHR**: Source: BLS, Barnichon (2010). This measure is defined as vacancies / effective searchers, where effective searchers are computed based on Abraham et al. (2020) as described in Section A.1 for 1994:q1-2024:q4. Vacancies are from JOLTS for 2001:q1-2024:q4 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1994:q1-2000:q4. Availability: 1994:q1-2024:q4.

- **V/ES-S**: Source: BLS, Barnichon (2010). This measure is defined as vacancies / effective searchers, where effective searchers are defined as in Şahin (2020) and shown in equation (6). Specifically, $ES-S = U_s + 0.48 \cdot U_l + 0.4 \cdot N^{\text{want}} + 0.09 \cdot N^{\text{do not want}} + 0.07E$. Here, U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, N^{want} is the share of workers not in the labor force that want to work, $N^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and E is the share of employed workers. 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. N^{want} are marginally attached workers 16 years and older and $N^{\text{do not want}}$ are workers not in the labor force that are not marginally attached; these can be computed from CPS data beginning in 1994. The weights on the terms reflect the relative search intensities of these workers estimated by Abraham, Haltiwanger, and Rendell (2020), aggregated up to the broader labor force groups used. Vacancies are from JOLTS for 2001:q1-2024:q4 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1994:q1-2000:q4. Availability: 1994:q1-2024:q4.

- **V/ES-HSW**: Source: BLS, Barnichon (2010). This measure is defined as vacancies / effective searchers, where effective searchers are computed based on the worker groups in Hall and Schulhofer-Wohl (2018) using the same methodology as for V/ES-AHR. The worker groups are the same 13 groups of unemployed workers as for the AHR measure, plus workers out of the labor force who do not want to work, workers out of the labor force who want work but are not looking, and employed workers. We generate the measure using the CPS micro data in the same way as described in Section A.1 for 1994:q1-2024:q4. Vacancies are from JOLTS for 2001:q1-2024:q4 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1994:q1-2000:q4. Availability: 1994:q1-2024:q4.

- **R/ES**: Source: BLS, Davis et al. (2013). We obtain the recruiting intensity from Davis et al. (2013) from Jason Faberman's website: https://sites.google.com/view/jason-faberman/home/publications for 2001:q1-2024:q2. We construct measures of V/ES using recruiting intensity instead of vacancies in the numerator. These measures are written as R/ES. Availability: 2001:q1-2024:q2.

- **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: 1990:q2-2024:q4.

- **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 quarter. Availability: 1990:q2-2024:q4.

- **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: 1995q4-2024:q4.

- **Jobs-workers gap**: Source: BLS, Barnichon (2010). This measure is defined as (Vacancies – unemployment)/Labor force. Vacancies are from JOLTS for 2001:q1-2024:q4 and from the composite Help Wanted Index constructed by Barnichon (2010) for 1990:q2-2000:q4. Number of unemployed is the number of individuals from the noninstitutional, civilian population aged 16 or older reporting to be unemployed from the CPS. A high workers' gap suggests that there are many vacancies compared to unemployed workers and hence the labor market is relatively tight. Availability: 1990:q2-2024:q4.

- **Aggregate Hours Gap**: Source: Faberman et al. (2020). We obtain the data from Jason Faberman for 1994:q1-2024:q4. The aggregate hours gap measures the difference between the number of hours people would like to work and the number of hours they actually work, averaged across the working-age population. It combines information on the unemployed who have a full gap between desired and actual hours, the underemployed who work part time but want more hours, and those out of the labor force who still want a job. Each group is weighted by its prevalence and average desired hours so the result is a single hours based measure of labor underutilization rather than just a headcount. We take the "AHG_total_rate." Availability: 1994:q1-2024:q4.

- **Non-Employment Index (NEI)**: Source: Hornstein et al. (2014). We obtain the data from https://www.richmondfed.org/research/national_economy/non_employment_index. We use the series that does not add the individuals that are working part time but would like to work full time. The non-employment index assigns every non-employed person a weight based on their historical probability of finding a job in the near future. Short term unemployed have high weights, long term unemployed have lower weights, and people far from the labor market have very low weights. Adding up these weighted shares produces an index that reflects the effective amount of nonemployed workers that could realistically transition into work and can therefore be leveraged to better describe the employment rate of the economy. Availability: 1994:q1-2024:q4.

- **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:q4 and from the data by Davis et al. (2012) for 1990:q2-2000:q4. Availability: 1990:q2-2024:q4.

- **Vacancies/Hires ratio:** Source: BLS, Davis et al. (2012), Barnichon (2010). This is a measure of the job filling rate for firms, computed as 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:q4 and from the data by Davis et al. (2012) for 1990:q2-2000:q4. Availability: 1990:q2-2024:q4.

- **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: 1993q2-2024:q4.

- **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: 1990:q2-2024:q4.

- **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: 1990:q2-

2024:q4.

A.3 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 to allow researchers to replicate our 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 1990:q2 and 2010:q2 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 2001:q1 to today, available from FRED as JTS1000QUL over USPRIV. We generate a new series of quits as quitsDFH between 1990:q2 and 2000:q4, use the average of the FRED quits rate and quitsDFH from 2001:q1 to 2010:q2, and use the FRED quits rate (100*JTS1000QUL/USPRIV) from 2010:q3 until today. This measure matches the quits rate JTS1000QUR but with higher precision.

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 1980-2001:q1, the simple average of the current ECI and the historical ECI for 2001:q2 to 2005:q4, and the current ECI from 2006:q1 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. For the HPW, we define effective searchers as in Şahin (2020) 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 1951:m1 to 2021:m8, 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 1990:q1 and 2000q3, use the average of the JOLTS vacancies and V_hwi from 2000:q4 to 2021:q3, and use JOLTS vacancies for 2021q4 until today. We compute vacancies over effective searchers as V/ES-S = vacancies / ES.

To compute the HPW, we keep the data between 1994:q1 and 2024:q4, and run a simple linear regression of the 3m ECI changes on V/ES-S and the quits rate. The non-standardized HPW index is $HPW_{nosd} = \beta_1 * V/ES_{S,t} + \beta_2 * Q_t$, where β_1 and β_2 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 1, 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 1994:q1 and 2024:q4, we can only use the lead quarter or the lag quarter, respectively, for the smoothing. We standardize the smoothed ECI as $ECI_{smoothed(sd)} = (ECI_{smoothed} - MEAN(ECI_{smoothed}))/SD(ECI_{smoothed})$.

B Additional Labor Market Tightness Figures

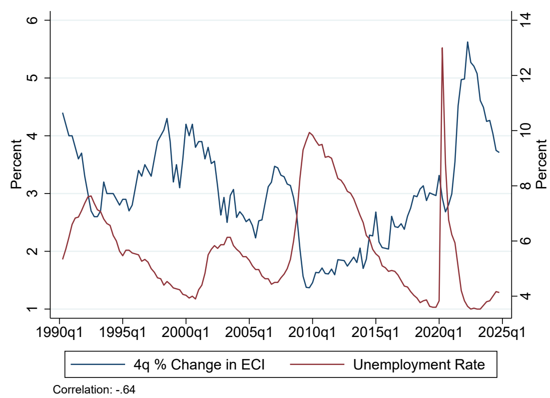
In this section, we illustrate the time series variation in several labor market tightness measures and how they correlate with wage growth. We also examine the correlation between the quits rate and vacancies per effective searcher. Section B.1 presents the time series variation of tightness with wage growth. Section B.2 analyzes the correlation of the quits rate with vacancies per effective searcher.

B.1 Time Series of Tightness and Wage Growth

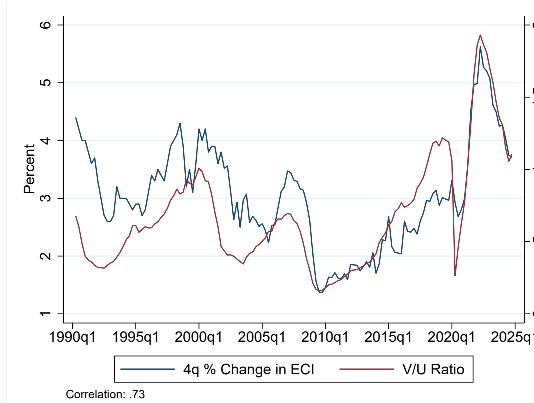
Panel (a) of Figure A.1 plots the time series of unemployment and the 12-month wage growth from the Employment Cost Index (ECI). While unemployment is negatively correlated with wage growth (correlation: -0.64), panel (b) shows that the ratio of vacancies to unemployment is more strongly correlated with wage growth (correlation: 0.73). Panels (c) and (d) illustrate the tight relationship between the quits rate and vacancies over effective searchers with wage growth (correlation of 0.81 and 0.80, respectively). We construct V/ES in this figure using the measure of effective searchers by Şahin (2020), results are similar using the AHR measure.

Figure A.1: Wage Growth versus Labor Market Conditions

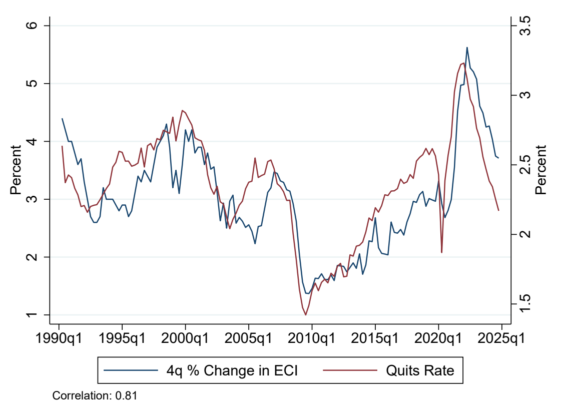
(a) Unemployment



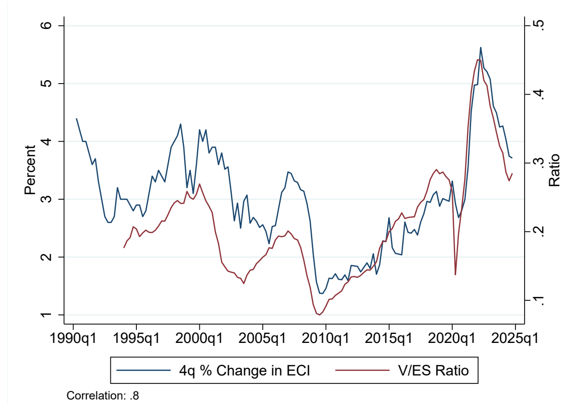
(b) Vacancy-Unemployment Ratio



(c) Quits Rate



(d) V/ES-S



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:q4. 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:q4 and from Davis et al. (2012) for 1990:q2-2000:q4. V/ES-S is constructed as the ratio of vacancies to effective searchers, where the latter are computed as $ES-S = U_s + 0.48 \cdot U_l + 0.4 \cdot N^{\text{want}} + 0.09 \cdot N^{\text{do not want}} + 0.07E$, where U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, N^{want} is the share of workers not in the labor force that want to work, $N^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and E 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 aggregated to broader worker groups by Şahin (2020).

B.2 Correlation between the Quits Rate and V/ES

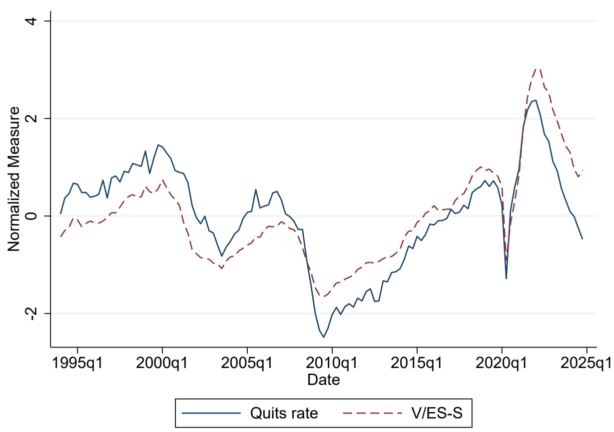
We compare the two series that make up our index: the quits rate and V/ES-S, both in the time series and in a scatter plot relationship in Figure A.2.

Panel (a) shows that both quits and V/ES-S show clear cyclical co-movement. They both fall sharply during recessions, with pronounced declines in 2001 and especially in 2008–2009, when quits dropped to record lows and V/ES-S collapsed. The recovery in the 2010s was gradual, with both measures returning to pre-recession levels only in the mid-2010s, after which they continued to rise and reached historic highs in the tight labor market of 2018–2019. The pandemic period brought an unprecedented collapse in early 2020 followed by a rapid rebound, with both quits and vacancies per effective searcher hitting series highs in 2021–2022 before easing somewhat as conditions cooled in 2023–2024. The two series track each other closely through most of this history, with only short-lived divergences.

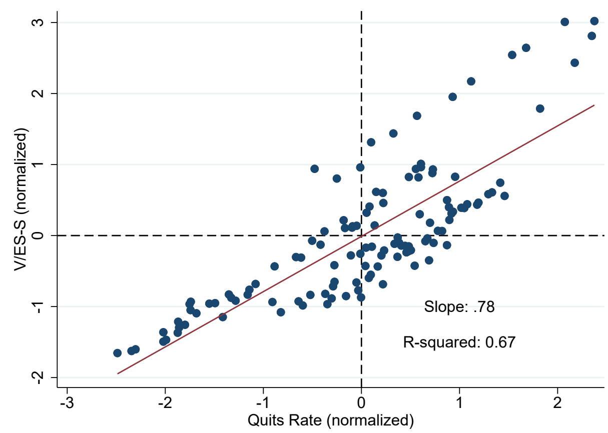
Panel (b) shows that there is a clear upward-sloping relationship (slope=0.78), reflecting their strong correlation across the cycle. The bulk of observations lie along a stable curve where higher vacancy pressure is associated with higher quits, consistent with standard matching models in which tight markets improve outside options and raise voluntary turnover. Deviations from the curve tend to occur in hot labor markets, as vacancies per effective searcher react even more strongly in procyclical shifts. Overall, this section shows the complementary nature of these two measures and highlights that they are not perfectly correlated.

Figure A.2: Quits and V/ES

a) Quits and V/ES-S Time Series



b) Quits and V/ES-S Scatter



Notes: Panel (a) plots the time series of the quits rate and of V/ES-S, and Panel (b) plots the relationship between the two variables with a fitted line, where the line fit comes from a regression V/ES-S$_t = \beta_0 + \beta_1 Quits_t + u_t$. The fitted value $\hat{\beta}_1$ is plotted and the slope and R-squared are reported. Vacancies are obtained from JOLTS for 2001:q1-2024:q4. 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:q4 and from Davis et al. (2012) for 1990:q2-2000:q4. V/ES-S is constructed as the ratio of vacancies to effective searchers, where the latter are computed as ES $= U_s + 0.48 \cdot U_l + 0.4 \cdot N^{\text{want}} + 0.09 \cdot N^{\text{do not want}} + 0.07E$ as in Şahin (2020). Measures are normalized for ease of interpretation to have mean 0 and standard devation 1.

C Tightness Measures and Detailed Regresions

This section presents the detailed regression results underlying the results in Tables 1 - 2 and Table 5 of the main text, and contains additional robustness analysis. Table A.1 shows the detailed results from running equation (7) for 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. The variables in the table are ordered by their R-squared. These results underlie Table 1 in the main text.

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 two measures of vacancies over effective searchers have the greatest standardized coefficients and R-squared coefficients. Thus, while each of the alternative indicators provides 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.[13] The results are in Table A.2. These regressions underlie the results in Table 2 in the main text. We find 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 the vacancies per effective searchers measures and, with a smaller coefficient, the aggregate hours gap. The results suggest that once the quits rate is accounted for, there is little additional information in most other indicators of labor market tightness.

Table A.3 shows that our results are robust to alternative measures of vacancies per searcher. First, we compute using the CPS micro data an alternative measure of effective searchers using the 16 worker groups in Hall and Schulhofer-Wohl (2018). We refer to the associated measure of labor market tightness as V/ES-HSW. Second, we recompute the mass of effective searchers with the 22 groups of Abraham, Haltiwanger, and Rendell (2020) using each group's job finding rate from

[13] 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.

1999 or in 2013 as a weight in equation (5), instead of job finding rates in 2006. Third, we compute alternative measures of tightness using the measure of recruiting intensity from Davis, Faberman, and Haltiwanger (2013) instead of vacancies in the numerator. Since recruiting intensity is only available from 2001:q1–2024:q2, we restrict all regressions in the table to the period of 2001:q1–2024:q2 to make the results comparable. We find that the fit across the different measures using vacancies in the numerator is relatively similar, but best for our baseline measure V/ES-AHR. The tightness measures using recruitment intensity instead of vacancies have a worse fit than the vacancy-based measures.

Table A.4 repeats the bivariate regressions using quits and one extra variable on the right-hand side. As before, the vacancy-based measures produce relatively similar results, with the V/ES-AHR measure performing best. In the regressions using recruiting intensity, the coefficient on the quits rate is strong and positive while the coefficient on the tightness measure is near zero and insignificant.

We next analyze whether the relationships still hold when we include in specification (7) a linear time trend as an additional right-hand side variable. The results in Table A.5 show that the measures of vacancies per searcher and the quits rate are still among the best trackers of wage growth. The two measures of vacancies per searcher now perform best, while the quits rate follows narrowly below the simple measure of V/U. In the bivariate regressions in Table A.6 which include quits and one other tightness variable, the combination of quits and vacancies per searcher performs best, and notably better than V/U and quits.

As an alternative, we re-run the baseline regressions with detrended right-hand side variables. Specifically, in the first stage we regress each tightness measure on a linear time trend:

$$X_t = \beta_0 + \beta_1 \cdot t + \epsilon_t, \tag{15}$$

and use the residual from this regression, $\hat{\epsilon}_t$, as our tightness measure. We then run the same regressions of wage growth on tightness as before. Results in Table A.7 are similar to the ones obtained when we included a linear trend on the right-hand side: the two measures of vacancies per searcher perform best, while the quits rate follows narrowly below the simple measure of V/U. In the bivariate regressions of Table A.8, the combination of the quits rate and vacancies per effective searcher performs best, and better than the combination of quits rate and V/U.

We next analyze whether our findings also hold when we restrict our sample to earlier time periods. We begin with the period 1990:q2-2014:q4 and then consider the period 1990:q2-2019:q4. Table A.9 shows the results for the period 1990:q2-2014:q4. Over this period, the job finding rate has the best in-sample fit, followed by the vacancies per searcher measures and the quits rate. In Table A.10, we extend the period to 2019:q4. The quits rate still performs well, but the vacancies per searcher measures have a lower fit, although still above the traditional V/U measure and the unemployment rate. The relatively weaker performance of the vacancies per searcher measures in the period between 2015 and 2019 is consistent with the out-of-sample forecasts in Figure 2, which show that the job finding rate and the aggregate hours gap have a particularly good out-of-sample performance in these years. However, the performance of these indicators deteriorates significantly in the post-COVID period, and the job finding rate is actually one of the worst indicators in terms of out-of-sample performance after 2020.

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

$$\Pi_t^{w,12} = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{16}$$

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 A.11 shows the results from these regressions. As before, the quits rate and measures of V/ES have the greatest standardized coefficients and fit, explaining about two-thirds of the variation in wage growth.

We finally turn to the three sets of regressions in Table 5 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.12, A.13, and A.14 report the detailed regression results. We again find consistently that quits and HPW outperform other measures, with HPW always with the highest coefficient and R^2.

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

Indep. Var.	(1) Quits Rate	(2) V/ES-AHR	(3) V/ES-S	(4) Agg. Hours Gap	(5) Jobs-Workers Gap
Y = Wage Growth	0.199***	0.200***	0.199***	-0.188***	0.177***
	(0.015)	(0.015)	(0.016)	(0.024)	(0.022)
Observations	139	124	124	124	139
R-squared	0.550	0.528	0.520	0.466	0.437
Indep. Var.	(6) V/U	(7) NFIB Difficulty Hiring	(8) CB Jobs Availability	(9) Vacancy/Hire	(10) Non-Employment Indexoyment Index
Y = Wage Growth	0.172***	0.174***	0.170***	0.169***	-0.171***
	(0.022)	(0.026)	(0.029)	(0.028)	(0.034)
Observations	139	127	139	139	124
R-squared	0.408	0.407	0.400	0.397	0.384
Indep. Var.	(11) Job Finding Rate	(12) Unemployment	(13) Acceptance Rate	(14) Hires Rate	(15) Continuing Claims
Y = Wage Growth	0.163***	-0.157***	-0.154***	0.119***	-0.117***
	(0.017)	(0.024)	(0.026)	(0.029)	(0.039)
Observations	139	139	117	139	139
R-squared	0.370	0.342	0.300	0.196	0.189
Indep. Var.	(16) Separation Rate				
Y = Wage Growth	-0.015				
	(0.038)				
Observations	139				
R-squared	0.003				

Notes: Table shows results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

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

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) Acceptance Rate	(4) Agg. Hours Gap	(5) Non-Employment Index
Y = Wage Growth	0.089***	0.085***	0.026	-0.059**	-0.033
	(0.028)	(0.029)	(0.023)	(0.029)	(0.024)
Quits Rate	0.129***	0.132***	0.219***	0.154***	0.175***
	(0.025)	(0.026)	(0.023)	(0.033)	(0.027)
Observations	124	124	117	124	124
R-squared	0.608	0.604	0.597	0.589	0.579

Indep. Var.	(6) NFIB Difficulty Hiring	(7) Vacancy/Hire	(8) V/U	(9) Job Finding Rate	(10) Jobs-Workers Gap
Y = Wage Growth	0.017	0.048*	0.048*	0.025	0.027
	(0.035)	(0.027)	(0.029)	(0.028)	(0.042)
Quits Rate	0.185***	0.164***	0.163***	0.180***	0.176***
	(0.031)	(0.022)	(0.024)	(0.034)	(0.038)
Observations	127	139	139	139	139
R-squared	0.573	0.564	0.563	0.553	0.552

Indep. Var.	(11) Separation Rate	(12) Hires Rate	(13) Continuing Claims	(14) CB Jobs Availability	(15) Unemployment
Y = Wage Growth	0.011	-0.012	-0.001	0.001	0.000
	(0.020)	(0.026)	(0.020)	(0.037)	(0.031)
Quits Rate	0.201***	0.207***	0.198***	0.198***	0.199***
	(0.016)	(0.024)	(0.019)	(0.036)	(0.030)
Observations	139	139	139	139	139
R-squared	0.551	0.551	0.550	0.550	0.550

Notes: Table shows results from regression (8) of 3-month wage changes from the ECI on tightness measures and the quits rate: $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.3: Wage Growth Regressions with Alternative Measures of Vacancies Per Searcher

Indep. Var.	(1) V/ES-AHR	(2) V/ES-1999	(3) V/ES-HSW	(4) V/ES-2013	(5) V/ES-S
Y = Wage Growth	0.195***	0.193***	0.193***	0.193***	0.193***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	94	94	94	94	94
R-squared	0.615	0.608	0.608	0.607	0.606
Indep. Var.	(6) R/ES-S	(7) R/ES-AHR	(8) R/ES-HSW		
Y = Wage Growth	0.174***	0.170***	0.151***		
	(0.031)	(0.031)	(0.033)		
Observations	94	94	94		
R-squared	0.389	0.372	0.292		

Notes: Table shows results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 2001:q1–2024:q2, when the recruiting intensity measure is available. V/ES-AHR and V/ES-S are defined in Appendix A. V/ES-1999 and V/ES-2013 use the job finding rates from 1999 and 2013, respectively, to define ES according to Abraham et al. (2020). V/ES-HSW uses the worker groups defined by Hall and Schulhofer-Wohl (2018). R/ES-S, R/ES-AHR, and R/ES-HSW use recruiting intensity from Davis, Faberman, and Haltiwanger (2013) instead of vacancies in the numerator. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.4: Bivariate Wage Growth Regressions with V/ES and R/ES Measures

Indep. Var.	(1) V/ES-AHR	(2) V/ES-2013	(3) V/ES-1999	(4) V/ES-HSW	(5) V/ES-S
Y = Wage Growth	0.076*	0.072*	0.072*	0.071*	0.070*
	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)
Quits Rate	0.140***	0.144***	0.143***	0.144***	0.145***
	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)
Observations	94	94	94	94	94
R-squared	0.682	0.681	0.681	0.680	0.679
Indep. Var.	(6) R/ES-S	(7) R/ES-HSW	(8) R/ES-AHR		
Y = Wage Growth	-0.024	-0.017	-0.009		
	(0.034)	(0.029)	(0.031)		
Quits Rate	0.226***	0.219***	0.215***		
	(0.031)	(0.027)	(0.029)		
Observations	94	94	94		
R-squared	0.664	0.663	0.661		

Table shows results from regression (8) of 3-month wage changes from the ECI on tightness measures and the quits rate: $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 2001:q1–2024:q2, when the recruiting intensity measure is available. V/ES-AHR and V/ES-S are defined in Appendix A. V/ES-1999 and V/ES-2013 use the job finding rates from 1999 and 2013, respectively, to define ES according to Abraham et al. (2020). V/ES-HSW uses the worker groups defined by Hall and Schulhofer-Wohl (2018). R/ES-S, R/ES-AHR, and R/ES-HSW use recruiting intensity from Davis, Faberman, and Haltiwanger (2013) instead of vacancies in the numerator. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.5: Wage Growth with Tightness Regressions with Linear Trend

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) V/U	(4) Quits Rate	(5) Jobs-Workers Gap
Y = Wage Growth	0.239*** (0.012)	0.238*** (0.012)	0.232*** (0.014)	0.199*** (0.015)	0.203*** (0.022)
Observations	124	124	139	139	139
R-squared	0.615	0.609	0.558	0.550	0.503

Indep. Var.	(6) Agg. Hours Gap	(7) Job Finding Rate	(8) NFIB Difficulty Hiring	(9) CB Jobs Availability	(10) Vacancy/Hire
Y = Wage Growth	-0.191*** (0.023)	0.209*** (0.020)	0.201*** (0.025)	0.189*** (0.025)	0.172*** (0.029)
Observations	124	139	127	139	139
R-squared	0.477	0.468	0.461	0.449	0.405

Indep. Var.	(11) Non-Employment Index	(12) Hires Rate	(13) Unemployment	(14) Acceptance Rate	(15) Continuing Claims
Y = Wage Growth	-0.171*** (0.034)	0.238*** (0.050)	-0.161*** (0.023)	-0.154*** (0.024)	-0.117*** (0.040)
Observations	124	139	139	117	139
R-squared	0.384	0.383	0.353	0.300	0.190

Indep. Var.	(16) Separation Rate
Y = Wage Growth	-0.051 (0.036)
Observations	139
R-squared	0.013

Notes: Table shows results from regression of 3-month wage changes from the ECI on tightness measures and a linear time trend: $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 \cdot t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.6: Bivariate Wage Growth with Tightness Regressions with Linear Trend

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) Acceptance Rate	(4) Agg. Hours Gap	(5) Non-Employment Index
Y = Wage Growth	0.176***	0.169***	0.033*	-0.061***	-0.024
	(0.047)	(0.051)	(0.019)	(0.021)	(0.022)
Quits Rate	0.057	0.063	0.225***	0.154***	0.182***
	(0.041)	(0.043)	(0.019)	(0.026)	(0.023)
Observations	124	124	117	124	124
R-squared	0.620	0.615	0.602	0.601	0.586

Indep. Var.	(6) V/U	(7) NFIB Difficulty Hiring	(8) Vacancy/Hire	(9) Job Finding Rate	(10) Separation Rate
Y = Wage Growth	0.130***	-0.039	0.048*	0.057	0.042
	(0.050)	(0.040)	(0.027)	(0.038)	(0.045)
Quits Rate	0.097**	0.231***	0.163***	0.156***	0.206***
	(0.047)	(0.037)	(0.023)	(0.039)	(0.016)
Observations	139	127	139	139	139
R-squared	0.583	0.582	0.564	0.559	0.558

Indep. Var.	(11) Jobs-Workers Gap	(12) Hires Rate	(13) CB Jobs Availability	(14) Unemployment	(15) Continuing Claims
Y = Wage Growth	0.046	-0.040*	-0.006	0.002	-0.001
	(0.046)	(0.023)	(0.038)	(0.030)	(0.020)
Quits Rate	0.159***	0.223***	0.204***	0.201***	0.199***
	(0.046)	(0.021)	(0.039)	(0.030)	(0.019)
Observations	139	139	139	139	139
R-squared	0.554	0.553	0.550	0.550	0.550

Notes: Table shows results from regression of 3-month wage changes from the ECI on tightness measures, the quits rate, and a linear time trend: $\Pi^w_t = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \beta_3 \cdot t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.7: Wage Growth with Detrended Tightness Regressions

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) V/U	(4) Quits Rate	(5) Jobs-Workers Gap
Y = Wage Growth	0.239***	0.238***	0.232***	0.199***	0.203***
	(0.013)	(0.013)	(0.014)	(0.015)	(0.021)
Observations	124	124	139	139	139
R-squared	0.612	0.606	0.558	0.550	0.503

Indep. Var.	(6) Agg. Hours Gap	(7) Job Finding Rate	(8) NFIB Difficulty Hiring	(9) CB Jobs Availability	(10) Vacancy/Hire
Y = Wage Growth	-0.191***	0.209***	0.201***	0.189***	0.172***
	(0.024)	(0.020)	(0.025)	(0.025)	(0.028)
Observations	124	139	127	139	139
R-squared	0.475	0.468	0.459	0.449	0.404

Indep. Var.	(11) Hires Rate	(12) Non-Employment Index	(13) Unemployment	(14) Acceptance Rate	(15) Continuing Claims
Y = Wage Growth	0.238***	-0.171***	-0.161***	-0.154***	-0.117***
	(0.050)	(0.035)	(0.023)	(0.024)	(0.040)
Observations	139	124	139	117	139
R-squared	0.383	0.382	0.353	0.299	0.190

Indep. Var.	(16) Separation Rate
Y = Wage Growth	-0.051
	(0.037)
Observations	139
R-squared	0.013

Notes: Table shows results from regression (7) of 3-month wage changes from the ECI on detrended tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$, where detrending is done as described in the text. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.8: Bivariate Wage Growth with Detrended Tightness Regressions

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) Acceptance Rate	(4) Agg. Hours Gap	(5) V/U
Y = Wage Growth	0.187***	0.181***	0.032	-0.065**	0.130***
	(0.051)	(0.054)	(0.021)	(0.027)	(0.048)
Quits Rate	0.047	0.052	0.223***	0.149***	0.097**
	(0.043)	(0.045)	(0.022)	(0.031)	(0.046)
Observations	124	124	117	124	139
R-squared	0.616	0.611	0.598	0.593	0.583

Indep. Var.	(6) Non-Employment Index	(7) NFIB Difficulty Hiring	(8) Vacancy/Hire	(9) Job Finding Rate	(10) Separation Rate
Y = Wage Growth	-0.028	-0.029	0.049*	0.057	0.042
	(0.024)	(0.042)	(0.027)	(0.038)	(0.044)
Quits Rate	0.178***	0.221***	0.163***	0.156***	0.206***
	(0.028)	(0.041)	(0.023)	(0.039)	(0.016)
Observations	124	127	139	139	139
R-squared	0.577	0.573	0.564	0.559	0.558

Indep. Var.	(11) Jobs-Workers Gap	(12) Hires Rate	(13) CB Jobs Availability	(14) Unemployment	(15) Continuing Claims
Y = Wage Growth	0.046	-0.039*	-0.005	0.002	-0.001
	(0.048)	(0.021)	(0.039)	(0.030)	(0.019)
Quits Rate	0.159***	0.223***	0.203***	0.200***	0.198***
	(0.047)	(0.020)	(0.040)	(0.031)	(0.019)
Observations	139	139	139	139	139
R-squared	0.554	0.552	0.550	0.550	0.550

Notes: Table shows results from regression (8) of 3-month wage changes from the ECI on detrended tightness measures and the detrended quits rate: $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$, where detrending is done as described in the text. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.9: Wage Growth with Tightness Regressions, 1990:q2-2014:q4

Indep. Var.	(1) Job Finding Rate	(2) Quits Rate	(3) V/ES-AHR	(4) V/ES-S	(5) Agg. Hours Gap
Y = Wage Growth	0.169***	0.179***	0.301***	0.299***	-0.185***
	(0.011)	(0.014)	(0.032)	(0.033)	(0.016)
Observations	99	99	84	84	84
R-squared	0.555	0.501	0.501	0.491	0.490

Indep. Var.	(6) Non-Employment Index	(7) Hires Rate	(8) Jobs-Workers Gap	(9) Acceptance Rate	(10) V/U
Y = Wage Growth	-0.212***	0.156***	0.203***	-0.165***	0.291***
	(0.019)	(0.017)	(0.020)	(0.017)	(0.042)
Observations	84	99	99	77	99
R-squared	0.488	0.446	0.421	0.421	0.406

Indep. Var.	(11) NFIB Difficulty Hiring	(12) Unemployment	(13) CB Jobs Availability	(14) Continuing Claims	(15) Vacancy/Hire
Y = Wage Growth	0.194***	-0.175***	0.160***	-0.190***	0.139***
	(0.019)	(0.018)	(0.027)	(0.029)	(0.030)
Observations	87	99	99	99	99
R-squared	0.401	0.401	0.365	0.312	0.267

Indep. Var.	(16) Separation Rate
Y = Wage Growth	0.099***
	(0.036)
Observations	99
R-squared	0.103

Notes: Table shows results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2014:q4, or shorter horizons in the few cases where less data are available. Definitions of all measures can be found in Appendix A. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.10: Wage Growth with Tightness Regressions, 1990:q2-2019:q4

Indep. Var.	(1) Job Finding Rate	(2) Agg. Hours Gap	(3) Quits Rate	(4) Hires Rate	(5) Non-Employment Index
Y = Wage Growth	0.172***	-0.184***	0.173***	0.147***	-0.173***
	(0.011)	(0.016)	(0.014)	(0.018)	(0.021)
Observations	119	104	119	119	104
R-squared	0.540	0.467	0.459	0.411	0.376

Indep. Var.	(6) Acceptance Rate	(7) V/ES-AHR	(8) V/ES-S	(9) Unemployment	(10) CB Jobs Availability
Y = Wage Growth	-0.145***	0.203***	0.197***	-0.140***	0.133***
	(0.016)	(0.041)	(0.042)	(0.021)	(0.027)
Observations	97	104	104	119	119
R-squared	0.361	0.316	0.303	0.293	0.285

Indep. Var.	(11) Jobs-Workers Gap	(12) NFIB Difficulty Hiring	(13) Vacancy/Hire	(14) V/U	(15) Continuing Claims
Y = Wage Growth	0.145***	0.131***	0.131***	0.158***	-0.139***
	(0.027)	(0.026)	(0.030)	(0.048)	(0.027)
Observations	119	107	119	119	119
R-squared	0.272	0.246	0.231	0.204	0.201

Indep. Var.	(16) Separation Rate
Y = Wage Growth	0.075***
	(0.026)
Observations	119
R-squared	0.082

Notes: Table shows results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard error with four lagss are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2019:q4, or shorter horizons in the few cases where less data are available. Definitions of all measures can be found in Appendix A. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.11: 12-Month Wage Growth and Tightness Measures

Indep. Var.	(1) V/ES-AHR	(2) Quits Rate	(3) V/ES-S	(4) Agg. Hours Gap	(5) V/U
Y = Wage Growth	0.745***	0.724***	0.738***	-0.729***	0.654***
	(0.072)	(0.068)	(0.075)	(0.141)	(0.089)
Observations	124	139	124	124	139
R-squared	0.657	0.650	0.643	0.629	0.531
Indep. Var.	(6) Jobs-Workers Gap	(7) NFIB Difficulty Hiring	(8) CB Jobs Availability	(9) Job Finding Rate	(10) Vacancy/Hire
Y = Wage Growth	0.649***	0.640***	0.631***	0.628***	0.626***
	(0.106)	(0.108)	(0.123)	(0.077)	(0.117)
Observations	139	127	139	139	139
R-squared	0.522	0.495	0.493	0.489	0.486
Indep. Var.	(11) Acceptance Rate	(12) Non-Employment Index	(13) Unemployment	(14) Hires Rate	(15) Continuing Claims
Y = Wage Growth	-0.653***	-0.612***	-0.574***	0.459***	-0.411**
	(0.097)	(0.187)	(0.131)	(0.118)	(0.172)
Observations	117	124	139	139	139
R-squared	0.477	0.443	0.409	0.261	0.209
Indep. Var.	(16) Separation Rate				
Y = Wage Growth	0.034				
	(0.149)				
Observations	139				
R-squared	0.001				

Notes: Table shows results from regression (16) of 12-month wage changes from the ECI on tightness measures: $\Pi_t^{w,12} = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors with four lags are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

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

Indep. Var.	(1) HPW	(2) Quits Rate	(3) V/ES-AHR	(4) V/ES-S	(5) CB Jobs Availability
Y=Wage Growth	0.214***	0.202***	0.195***	0.195***	0.168***
	(0.012)	(0.015)	(0.018)	(0.018)	(0.029)
Observations	123	138	123	123	138
R-squared	0.610	0.575	0.506	0.503	0.397

Indep. Var.	(6) NFIB Difficulty Hiring	(7) Jobs-Workers Gap	(8) Vacancy/Hire	(9) V/U	(10) Agg. Hours Gap
Y=Wage Growth	0.172***	0.168***	0.167***	0.164***	-0.167***
	(0.026)	(0.024)	(0.027)	(0.023)	(0.031)
Observations	126	138	138	138	123
R-squared	0.396	0.396	0.391	0.379	0.367

Indep. Var.	(11) Acceptance Rate	(12) Non-Employment Index	(13) Job Finding Rate	(14) Unemployment	(15) Hires Rate
Y=Wage Growth	-0.157***	-0.146***	0.140***	-0.139***	0.126***
	(0.023)	(0.043)	(0.024)	(0.030)	(0.026)
Observations	116	123	138	138	138
R-squared	0.314	0.281	0.279	0.272	0.222

Indep. Var.	(16) Continuing Claims	(17) Separation Rate
Y=Wage Growth	-0.091*	-0.021
	(0.050)	(0.034)
Observations	138	138
R-squared	0.117	0.006

Notes: Table shows results from regression (10) of 3-month ahead wage changes from the ECI on tightness measures: $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t$, where h =1. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.13: 6-month Ahead Wage Growth with Tightness Measures

Indep. Var.	(1) HPW	(2) Quits Rate	(3) V/ES-S	(4) V/ES-AHR	(5) NFIB Difficulty Hiring
Y=Wage Growth	0.203***	0.191***	0.183***	0.183***	0.174***
	(0.014)	(0.016)	(0.021)	(0.021)	(0.025)
Observations	122	137	122	122	125
R-squared	0.553	0.520	0.443	0.443	0.402

Indep. Var.	(6) Vacancy/Hire	(7) CB Jobs Availability	(8) Jobs-Workers Gap	(9) V/U	(10) Acceptance Rate
Y=Wage Growth	0.166***	0.160***	0.152***	0.150***	-0.153***
	(0.025)	(0.027)	(0.027)	(0.025)	(0.018)
Observations	137	137	137	137	115
R-squared	0.384	0.362	0.326	0.317	0.300

Indep. Var.	(11) Agg. Hours Gap	(12) Hires Rate	(13) Job Finding Rate	(14) Unemployment	(15) Non-Employment Index
Y=Wage Growth	-0.147***	0.132***	0.124***	-0.117***	-0.120**
	(0.040)	(0.024)	(0.030)	(0.038)	(0.054)
Observations	122	137	137	137	122
R-squared	0.283	0.243	0.220	0.194	0.188

Indep. Var.	(16) Continuing Claims	(17) Separation Rate
Y=Wage Growth	-0.067	-0.012
	(0.059)	(0.033)
Observations	137	137
R-squared	0.062	0.002

Notes: Table shows results from regression (10) of 6-month ahead wage changes from the ECI on tightness measures: $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t$, where h =2. Wage changes are rescaled into quarterly growth rates. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.14: 12-month Ahead Wage Growth with Tightness Measures

Indep. Var.	(1) HPW	(2) Quits Rate	(3) V/ES-S	(4) Vacancy/Hire	(5) V/ES-AHR
Y=Wage Growth	0.184***	0.177***	0.165***	0.159***	0.165***
	(0.015)	(0.013)	(0.025)	(0.023)	(0.025)
Observations	120	135	120	135	120
R-squared	0.454	0.451	0.353	0.352	0.349
Indep. Var.	(6) NFIB Difficulty Hiring	(7) CB Jobs Availability	(8) Acceptance Rate	(9) Jobs-Workers Gap	(10) V/U
Y=Wage Growth	0.160***	0.152***	-0.146***	0.137***	0.134***
	(0.025)	(0.024)	(0.017)	(0.023)	(0.025)
Observations	123	135	113	135	135
R-squared	0.341	0.325	0.271	0.263	0.249
Indep. Var.	(11) Hires Rate	(12) Agg. Hours Gap	(13) Job Finding Rate	(14) Unemployment	(15) Non-Employment Index
Y=Wage Growth	0.133***	-0.117***	0.106***	-0.100***	-0.095*
	(0.021)	(0.041)	(0.032)	(0.037)	(0.051)
Observations	135	120	135	135	120
R-squared	0.244	0.174	0.162	0.140	0.117
Indep. Var.	(16) Continuing Claims	(17) Separation Rate			
Y=Wage Growth	-0.040	-0.012			
	(0.067)	(0.028)			
Observations	135	135			
R-squared	0.023	0.002			

Notes: Table shows results from regression (10) of 12-month ahead wage changes from the ECI on tightness measures: $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \epsilon_t$, where h =4. Wage changes are rescaled into quarterly growth rates. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

D Industry-Level Regressions

This section focuses on industry-level regressions. We first expand on the regressions in the main text for Tables 3-4 and report more details underlying these regressions including observations and fixed effects. We then run the regressions without time fixed effects.

Table A.15 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.16 presents the estimated regression coefficients when we include both the quits rate and 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).

Tables A.17 and A.18 repeat the same regressions but omit time fixed effects from the specification. Since business cycle shocks are strongly correlated in the cross section, the inclusion of the time fixed effects may weaken the relationships between wage growth and tightness measures. The results are qualitatively similar to before. In particular, we still find that the quits rate and V/ES have the strongest correlation with wage growth individually, and that V/ES provides the most additional explanatory value for wage growth in bivariate regressions that include the quits rate.

Table A.15: Industry-Level Wage Growth Regressions

Indep. Var.	(1) Quits Rate	(2) V/ES	(3) Hires Rate	(4) Jobs-Workers Gap	(5) Unemployment
Y = Wage Growth	0.229***	0.127***	0.107*	0.075*	-0.058*
	(0.057)	(0.044)	(0.057)	(0.040)	(0.032)
Time FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	946	946	946	946	946
Within R-squared	0.020	0.010	0.005	0.004	0.003

Indep. Var.	(6) Separation Rate	(7) Vacancy/Hire	(8) V/U	(9) Job Finding Rate
Y = Wage Growth	-0.053**	0.035	0.013	0.003
	(0.026)	(0.035)	(0.028)	(0.033)
Time FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	946	946	946	946
Within R-squared	0.002	0.001	0.000	0.000

Notes: Table shows results from regression (9) of 3-month wage changes from the ECI on tightness measures at the industry-level: $\Pi^w_{it} = \beta_1 X_{it} + \gamma_i + \rho_t + \epsilon_{it}$. Independent variables are standardized to have zero mean and standard deviation of one. Driscoll-Kraay standard errors with one lag are included. All measures of tightness are ordered by their fit (Within R^2). Estimates use data from 2001:q1–2024:q4, when quits data are available. Definitions of all measures can be found in Appendix A, except for V/ES, which for industry measures uses $ES = U + 0.14E$. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.16: Bivariate Industry-Level Wage Growth Regressions

Indep. Var.	(1) V/ES	(2) Separation Rate	(3) Vacancy/Hire	(4) Jobs-Workers Gap	(5) Unemployment
Y = Wage Growth	0.085**	-0.059**	0.058	0.044	-0.038
	(0.038)	(0.025)	(0.038)	(0.032)	(0.026)
Quits Rate	0.200***	0.233***	0.238***	0.217***	0.222***
	(0.051)	(0.058)	(0.058)	(0.056)	(0.059)
Time FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	946	946	946	946	946
Within R-squared	0.024	0.023	0.022	0.022	0.021

Indep. Var.	(6) V/U	(7) Job Finding Rate	(8) Hires Rate
Y = Wage Growth	0.023	-0.004	0.006
	(0.027)	(0.034)	(0.045)
Quits Rate	0.231***	0.230***	0.226***
	(0.058)	(0.057)	(0.053)
Time FE	Y	Y	Y
Industry FE	Y	Y	Y
Observations	946	946	946
Within R-squared	0.021	0.020	0.020

Notes: Table shows results from regression (9) of 3-month wage changes from the ECI on tightness measures at the industry-level with the quits rate additionally included: $\Pi^w_{it} = \beta_1 X_{it} + \beta_2 Q_{it} + \gamma_i + \rho_t + \epsilon_{it}$. Independent variables are standardized to have zero mean and standard deviation of one. Driscoll-Kraay standard errors with one lag are included. All measures of tightness are ordered by their fit (Within R^2). Estimates use data from 2001:q1–2024:q4, when quits data are available. Definitions of all measures can be found in Appendix A, except for V/ES, which for industry measures uses $ES = U + 0.14E$. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.17: Industry-Level Wage Growth Regressions Without Time Fixed Effects

Indep. Var.	(1) Quits Rate	(2) V/ES	(3) Jobs-Workers Gap	(4) V/U	(5) Job Finding Rate
Y = Wage Growth	0.432***	0.204***	0.180***	0.166***	0.142***
	(0.043)	(0.030)	(0.035)	(0.028)	(0.027)
Time FE	N	N	N	N	N
Industry FE	Y	Y	Y	Y	Y
Observations	946	946	946	946	946
Within R-squared	0.155	0.113	0.095	0.083	0.066

Indep. Var.	(6) Vacancy/Hire	(7) Unemployment	(8) Hires Rate	(9) Separation Rate
Y = Wage Growth	0.178***	-0.192***	0.311***	-0.081*
	(0.046)	(0.050)	(0.114)	(0.042)
Time FE	N	N	N	N
Industry FE	Y	Y	Y	Y
Observations	946	946	946	946
Within R-squared	0.063	0.055	0.055	0.010

Notes: Table shows results from regression (9) of 3-month wage changes from the ECI on tightness measures at the industry-level without time fixed effects: $\Pi_{it}^{w} = \beta_1 X_{it} + \gamma_i + \epsilon_{it}$. Independent variables are standardized to have zero mean and standard deviation of one. Driscoll-Kraay standard errors with one lag are included. All measures of tightness are ordered by their fit (Within R^2). Estimates use data from 2001:q1–2024:q4, when quits data are available. Definitions of all measures can be found in Appendix A, except for V/ES, which for industry measures uses $ES = U + 0.14E$. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.18: Bivariate Industry-Level Wage Growth Regressions Without Time Fixed Effects

Indep. Var.	(1) V/ES	(2) V/U	(3) Vacancy/Hire	(4) Job Finding Rate	(5) Jobs-Workers Gap
Y = Wage Growth	0.079**	0.058**	0.062*	0.039*	0.040
	(0.032)	(0.026)	(0.035)	(0.021)	(0.029)
Quits Rate	0.336***	0.371***	0.387***	0.392***	0.380***
	(0.040)	(0.041)	(0.038)	(0.051)	(0.048)
Time FE	N	N	N	N	N
Industry FE	Y	Y	Y	Y	Y
Observations	946	946	946	946	946
Within R-squared	0.164	0.162	0.161	0.158	0.157

Indep. Var.	(6) Separation Rate	(7) Unemployment	(8) Hires Rate
Y = Wage Growth	-0.023	-0.027	0.006
	(0.024)	(0.023)	(0.038)
Quits Rate	0.426***	0.413***	0.429***
	(0.042)	(0.051)	(0.043)
Time FE	N	N	N
Industry FE	Y	Y	Y
Observations	946	946	946
Within R-squared	0.155	0.155	0.155

Notes: Table shows results from regression (9) of 3-month wage changes from the ECI on tightness measures at the industry-level with the quits rate additionally included, and without time fixed effects: $\Pi_{it}^{w} = \beta_1 X_{it} + \beta_2 Q_{it} + \gamma_i + \epsilon_{it}$. Independent variables are standardized to have zero mean and standard deviation of one. Driscoll-Kraay standard errors with one lag are included. All measures of tightness are ordered by their fit (Within R^2). Estimates use data from 2001:q1–2024:q4, when quits data are available. Definitions of all measures can be found in Appendix A, except for V/ES, which for industry measures uses $ES = U + 0.14E$. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

E Additional Robustness on Forecasting

In this section, we provide robustness analysis for our forecasting exercises. We first show that our in-sample forecasting exercises in Table 5 are robust to including lagged wage growth. We then repeat the out-of-sample forecasting exercise including current wage growth as an additional predictor, including a linear time trend, and using alternative measures of effective searchers.

We first show that the in-sample forecasting results in Table 5 are robust to including lagged wage growth. We focus on the three-month ahead wage growth regression, and include current ECI wage growth as an additional control in the regression. Thus, our specification now takes the form:

$$\Pi^w_{t+1} = \beta_0 + \beta_1 X_t + \beta_2 \Pi^w_t + \epsilon_t, \tag{17}$$

where Π^w_{t+1} is the three-month ahead wage growth, X_t is the standardized tightness measure of interest, and Π^w_t is the current three-month wage growth (between $t-1$ and t). Table A.19 presents a set of coefficients on regressions that includes these X_t variables alongside wage growth at time t. We again find that HPW is the strongest indicator in terms of both coefficient size and fit. Given HPW, quits, and V/ES, knowledge of current wage growth is an insignificant predictor of future wage growth. However, for all other measures, current wage growth still has important predictive power. This indicates the importance of using current wage growth only when sufficient tightness measures are not available.

We next repeat the out-of-sample forecasting exercise from Figure 2 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:

$$\Pi^w_{t+1} = \beta_0 + \beta_1 X_t + \beta_2 \Pi^w_t + \epsilon_t \text{ for } t < T. \tag{18}$$

where, as before, we only use data from the start of our sample to quarter T. This model now includes current wage growth, Π^w_t, as an additional predictor on the right-hand side. We take the fitted values from this regression model to get a predicted value for wage growth. Then, similar to the main text, we compute the RMSE over 40-quarter rolling windows. Figure A.3 presents the resulting fit for rolling windows ending in 2010:q1-2024:q4. We find that controlling for current wage growth does not change our main findings, as quits and HPW continue to outperform other measures significantly. Throughout the sample, they are among the strongest indicators, but they separate significantly after 2020 and remain the best predictors of future wage growth.

In Figure A.4, we repeat the baseline out-of-sample forecasting exercise but include a linear time trend in the regression equation (11). We again find similar conclusions on the relative strength of our measures, but find that the V/ES measures now perform significantly better in the post-COVID period. These measures now only have a slightly worse performance than the HPW index and the quits rate after 2020.

In Figure A.5, we analyze the out-of-sample forecasting performance of alternative measures of vacancies per effective searcher, using the same measures as in Appendix C. First, we compute using the CPS micro data an alternative measure of effective searchers using the 16 worker groups in Hall and Schulhofer-Wohl (2018) (V/ES-HSW). Second, we recompute the mass of effective searchers with the 22 groups of Abraham, Haltiwanger, and Rendell (2020) using each group's job finding rate from 1999 or in 2013 as a weight in equation (5), instead of job finding rates in 2006. Third, we compute alternative measures of tightness using the measure of recruiting intensity from Davis, Faberman, and Haltiwanger (2013) instead of vacancies in the numerator (R). We find that the different definitions of effective searchers do not substantially change the out-of-sample performance, but that using recruiting intensity instead of vacancies improves the fit in the pre-COVID period while worsening it in the post-COVID period.

Table A.19: 3-Month Ahead Wage Growth with Current Wage Growth Controls

Indep. Var.	(1) HPW	(2) Quits Rate	(3) V/ES-AHR	(4) V/ES-S	(5) NFIB Difficulty Hiring
Y = Wage Growth	0.233***	0.209***	0.171***	0.169***	0.125***
	(0.023)	(0.023)	(0.028)	(0.028)	(0.024)
Lagged Wage Growth	-0.089	-0.036	0.120	0.130	0.271***
	(0.076)	(0.077)	(0.098)	(0.099)	(0.088)
Observations	123	138	123	123	126
R-squared	0.613	0.575	0.513	0.511	0.439

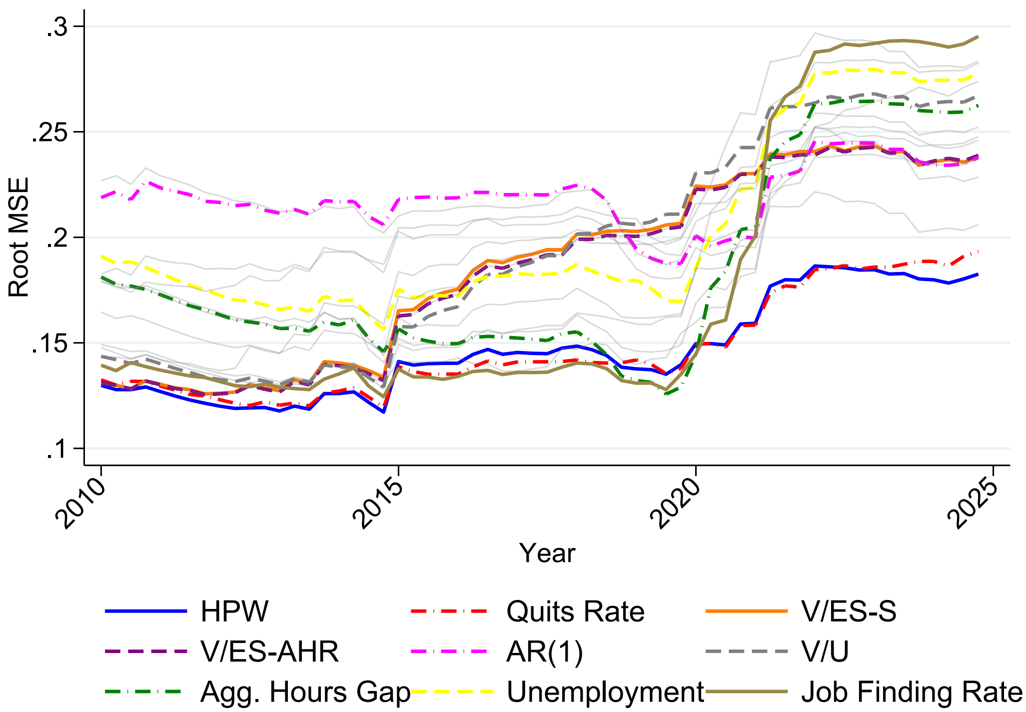
Indep. Var.	(6) CB Jobs Availability	(7) Vacancy/Hire	(8) Jobs-Workers Gap	(9) Acceptance Rate	(10) V/U
Y = Wage Growth	0.125***	0.124***	0.126***	-0.095***	0.119***
	(0.029)	(0.027)	(0.027)	(0.024)	(0.025)
Lagged Wage Growth	0.251**	0.257**	0.236**	0.406***	0.263***
	(0.100)	(0.098)	(0.100)	(0.127)	(0.094)
Observations	138	138	138	116	138
R-squared	0.435	0.432	0.428	0.428	0.421

Indep. Var.	(11) Aggregate Hours Gap	(12) Non-Employment Index	(13) Hires Rate	(14) Unemployment	(15) Job Finding Rate
Y = Wage Growth	-0.111***	-0.078*	0.075***	-0.081***	0.082**
	(0.041)	(0.042)	(0.023)	(0.030)	(0.039)
Lagged Wage Growth	0.298*	0.395***	0.419***	0.369***	0.359**
	(0.160)	(0.141)	(0.129)	(0.124)	(0.180)
Observations	123	123	138	138	138
R-squared	0.415	0.379	0.364	0.363	0.361

Indep. Var.	(16) Continuing Claims	(17) Separation Rate
Y = Wage Growth	-0.034	-0.014
	(0.038)	(0.016)
Lagged Wage Growth	0.490***	0.543***
	(0.118)	(0.097)
Observations	138	138
R-squared	0.316	0.305

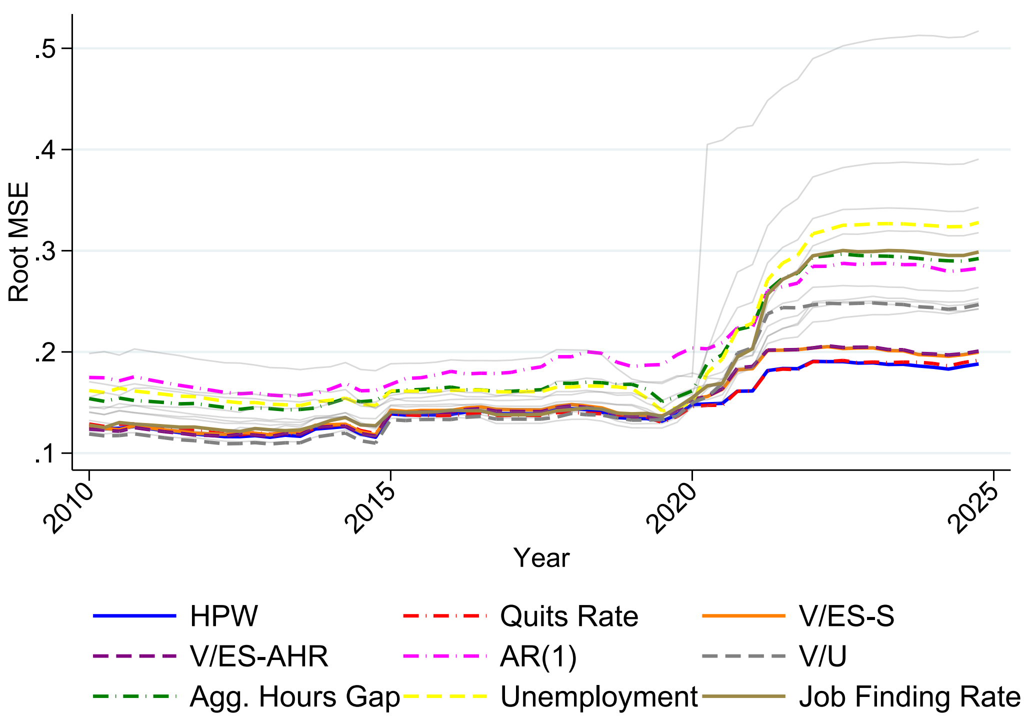
Notes: Table shows results from regression (10) of 3-month ahead wage changes from the ECI on tightness measures, where additionally we include current wage growth as control: $\Pi^w_{t,t+h} = \beta_0 + \beta_1 X_t + \beta_2 \Pi^w_t + \epsilon_t$, where h =1. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Figure A.3: Forward Wage Growth on Different Measures with Current Wage Growth Control, $RMSE$



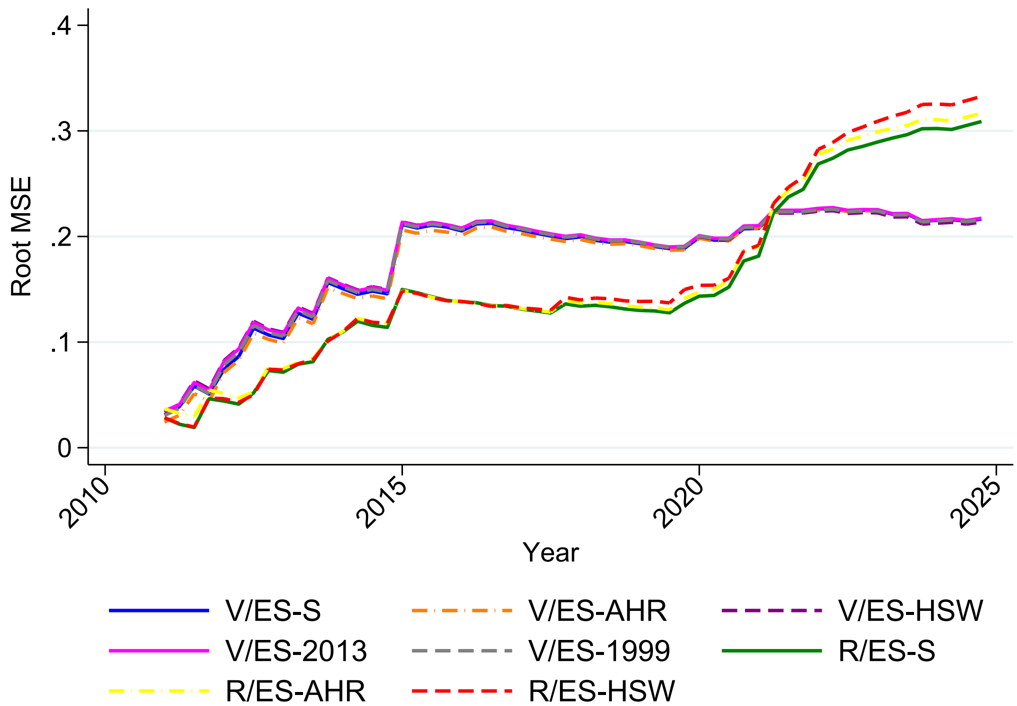
Notes: Figure plots the RMSE over 40-quarter rolling windows from one-period ahead out-of-sample 3-month wage changes from the ECI starting in 2004:q1 against the HPW index and other labor market indicators. All forecasting regressions now also allow for a lagged ECI wage growth term; see text for details. x-axis denotes the end of the 40-quarter rolling window. For ease of reading, we only add color to selected series.

Figure A.4: Forward Wage Growth on Different Measures with Trend Term, $RMSE$



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 2004:q1 against the HPW index and other labor market indicators. All forecasting regressions now also include a time trend. x-axis denotes the end of the 40-quarter rolling window. For ease of reading, we only add color to selected series.

Figure A.5: Forward Wage Growth on V/ES and R/ES 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 2004:q1. V/ES-AHR and V/ES-S are defined in Appendix A. V/ES-1999 and V/ES-2013 use the job finding rates from 1999 and 2013, respectively, to define ES according to Abraham et al. (2020). V/ES-HSW uses the worker groups defined by Hall and Schulhofer-Wohl (2018). R/ES-S, R/ES-AHR, and R/ES-HSW use recruiting intensity from Davis, Faberman, and Haltiwanger (2013) instead of vacancies in the numerator. x-axis denotes the end of the 40-quarter rolling window. For ease of reading, we only add color to selected series.

F Additional Nonlinearity Analysis

This section presents some additional empirical results examining nonlinearities in the relationship between wage growth and tightness in Section F.1. We show that theoretically it is possible that the relationship between wage growth and unemployment is nonlinear while the relationship between wage growth and vacancies per searcher is not in Section F.2.

F.1 Additional Empirical Results

In this section, we present additional details on our regressions analyzing nonlinearity in the wage Phillips curve. We start by evaluating the presence of nonlinearities formally. First, we run regressions of 3-month wage growth on the tightness measures similar to equation (7), 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:

$$\Pi_t^w = \beta_0 + \beta_1 \mathbb{I}(X_t > \gamma) + \beta_2 X_t + \beta_3 \mathbb{I}(X_t > \gamma) \cdot X_t + \epsilon_t. \tag{19}$$

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. If nonlinearity is present, we would expect $\beta_3 \neq 0$.

Table A.20 presents the results. Panel (a) repeats our baseline regressions for the four measures of labor market tightness. Panel (b) then runs the regressions with the additional threshold terms. The coefficient of interest is on $\mathbb{I}(X_t > \gamma) \cdot X_t$: 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 is quantitatively large, it is not significant at conventional levels. The coefficients are insignificant for the other tightness measures. There does appear to be a statistically significant level shift at the break point for V/ES-S, consistent with the parallel shift of the trend line in Figure 3, panel (d); 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. The fit of wage growth, measured by R-squared, only marginally improves when we add the threshold terms (see R^2 in panel (a) versus panel (b)).

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:

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \epsilon_t, \tag{20}$$

and present the results in panel (c) of Table A.20. The coefficient on the squared term is insignificant in all specifications, indicating again that we cannot reject a linear relationship, and the fit is very similar to the simple linear regression in panel (a).

We next examine whether we detect nonlinearities when we detrend the tightness variables. Trend movements in quits, vacancies, or labor force participation could move the tightness measures in a way that obscures the relationship between tightness and wage inflation. We regress each tightness measure on a linear time trend:

$$X_t = \beta_0 + \beta_1 \cdot t + \epsilon_t, \tag{21}$$

and then use the residual from this regression, $\hat{\epsilon}_t$, as our tightness measure. This variable shows the deviation of each tightness measure from its trend level, and therefore gives a sense of whether tightness is currently above or below its trend. Figure A.6 presents the relationship between the detrended tightness variables and wage inflation. Similar to the figure in the main text, we do not detect a nonlinear pattern. Table A.21 performs the same regressions as above with the detrended tightness measures. We detect some slight evidence of nonlinearities for the unemployment rate, which has a steeper relationship with wages when it is low, but not for the other variables. None of the other threshold coefficients or squared coefficients is significant, and the fit is similar to the fit in the linear regression. Moreover, for the detrended variables we do not find a level shift for V/ES at the break point in panel (b).

Finally, in our last exercise in nonlinearities, for completeness we study the role of nonlinearities with 12 additional variables in the main text that measure labor market tightness. This can be found in Figures A.7 and A.8. We study the threshold of high tightness (<25th percentile in variables that comove negatively with wage growth and > 75th percentile in variables that comove positively with wage growth). Overall, for some variables, the wage-tightness relationship does appear to be nonlinear: for the NFIB Index of the Difficulty Hiring, the Conference Board jobs availability measure, the job-workers gap, the vacancies/hires ratio, the NEI, and for continuing claims, wage growth increases more strongly with tightness when the labor market is tight than when it is slack.

Table A.20: Nonlinearities in Wage Growth Regressions

(a) Baseline Regressions

Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
Y = ECI Growth	0.199***	0.214***	0.199***	-0.157***
	(0.017)	(0.016)	(0.015)	(0.019)
Observations	124	124	139	139
R-squared	0.520	0.604	0.550	0.342

(b) Regressions with Threshold

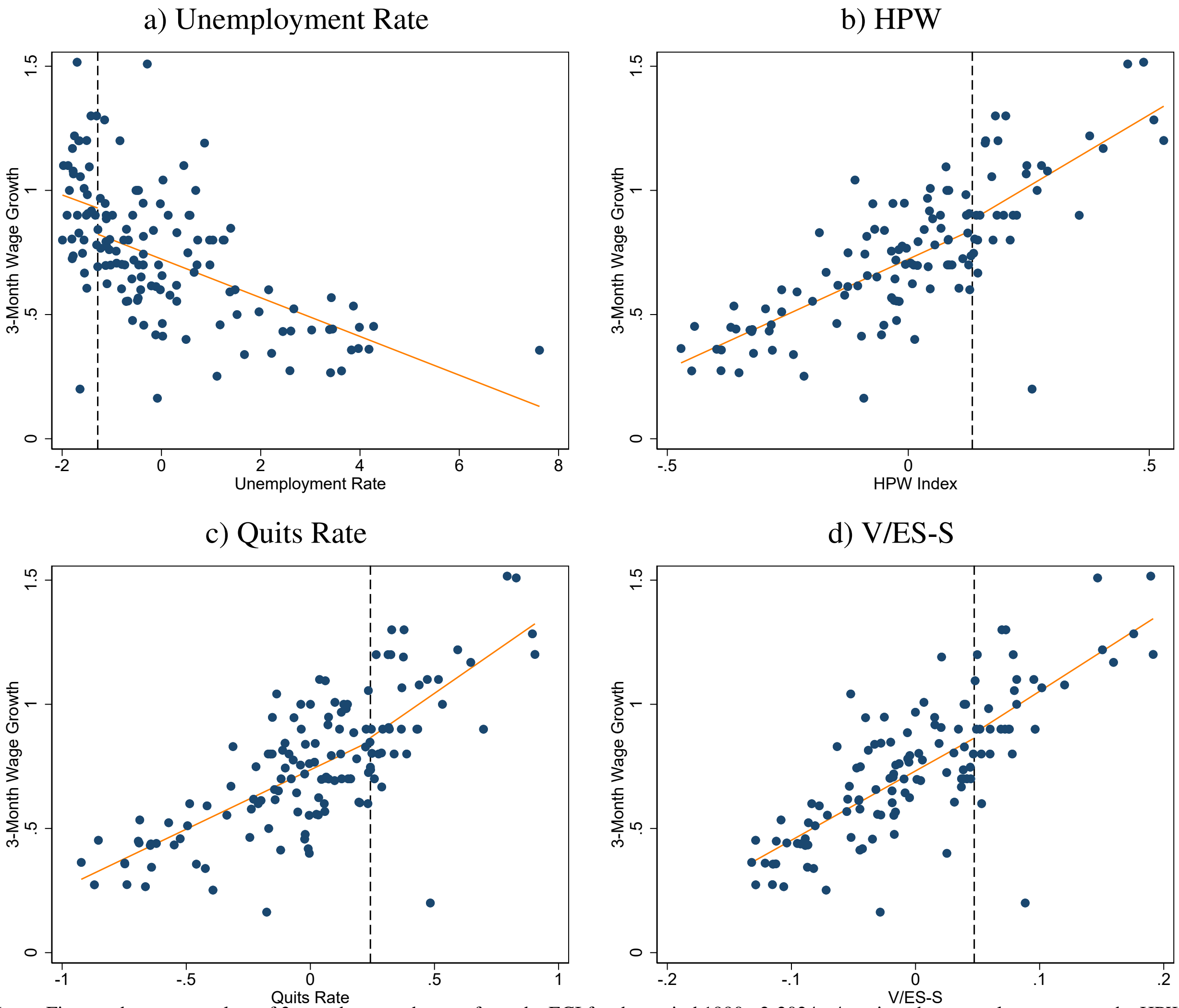
Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
Linear Term	0.185***	0.204***	0.178***	-0.486**
	(0.030)	(0.024)	(0.022)	(0.234)
$\mathbf{1}(X_t > \gamma)$	0.117**	-0.020.	-0.052.	0.302.
	(0.051)	(0.072)	(0.081)	(0.241)
$\mathbf{1}(X_t > \gamma) * X_t$	-0.038.	0.034.	0.090.	0.343.
	(0.045)	(0.056)	(0.065)	(0.235)
Observations	124	124	139	139
R-squared	0.540	0.605	0.558	0.355

(c) Regressions with Square

Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
X_t	0.209***	0.213***	0.204***	-0.176***
	(0.021)	(0.016)	(0.016)	(0.024)
Squared Term	-0.010.	0.010.	0.016.	0.016.
	(0.012)	(0.011)	(0.011)	(0.013)
Observations	124	124	139	139
R-squared	0.523	0.607	0.556	0.350

Notes: Panel 1 reports results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$. Panel 2 reports results from regression (19): $\Pi_t^w = \beta_0 + \beta_1 \mathbb{I}(X_t > \gamma) + \beta_2 X_t + \beta_3 \mathbb{I}(X_t > \gamma) \cdot X_t + \epsilon_t$. Panel 3 reports results from regression (20): $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Figure A.6: Nonlinearity in Tightness and Wage Growth with Main Variables (detrended)



Notes: Figures show scatterplots of 3-month wage changes from the ECI for the period 1990:q2-2024:q4 against the unemployment rate, the HPW index, the quits rate, and V/ES. Each tightness variable is detrended linearly as described in the text. Each dot indicates a quarterly observation. Dashed vertical lines denote the selected break point of the relationship, which is chosen as the 25th percentile of the values for unemployment and as the 75th percentile of the values for the HPW index, quits rate, and V/ES-S. Orange lines indicate the best linear fit to the left and to the right of the break point.

Table A.21: Nonlinearities in Wage Growth Regressions (detrended)

(a) Baseline Regressions

Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
Y = ECI Growth	0.215***	0.214***	0.199***	-0.159***
	(0.016)	(0.016)	(0.015)	(0.018)
Observations	124	124	139	139
R-squared	0.606	0.605	0.550	0.353

(b) Regressions with Threshold

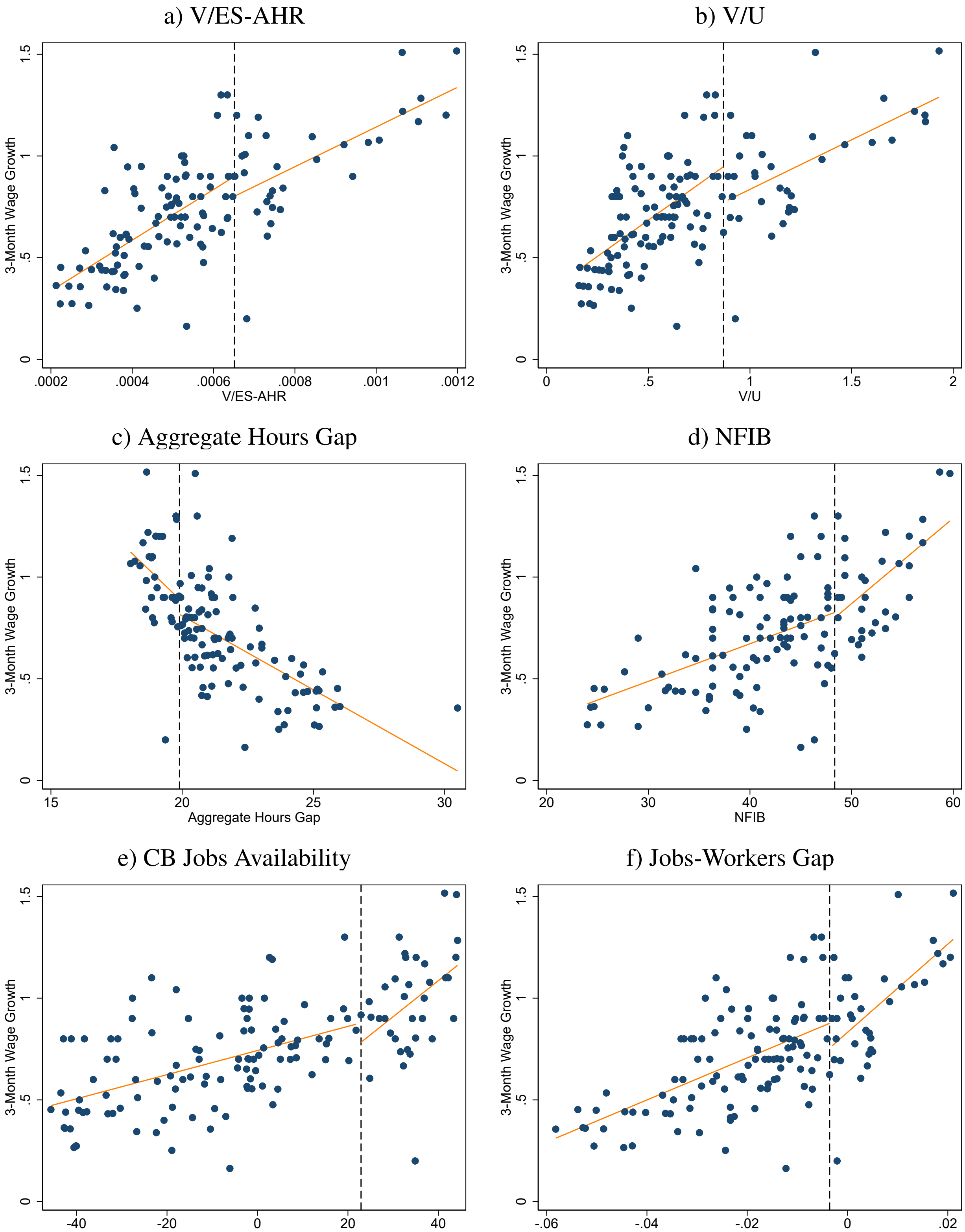
Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
X_t	0.202***	0.188***	0.177***	-0.267***
	(0.028)	(0.023)	(0.023)	(0.076)
$\mathbf{1}(X_t > \gamma)$	-0.013.	0.006.	-0.020.	0.029.
	(0.053)	(0.077)	(0.061)	(0.073)
$\mathbf{1}(X_t > \gamma) * X_t$	0.033.	0.056.	0.069.	0.131*
	(0.044)	(0.062)	(0.050)	(0.078)
Observations	124	124	139	139
R-squared	0.608	0.612	0.558	0.373

(c) Regressions with Square

Indep. Var.	(1) V/ES-S	(2) HPW	(3) Quits Rate	(4) Unemployment Rate
X_t	0.214***	0.216***	0.203***	-0.192***
	(0.016)	(0.016)	(0.016)	(0.025)
X_t^2	0.002.	0.016.	0.014.	0.023*
	(0.012)	(0.011)	(0.011)	(0.013)
Observations	124	124	139	139
R-squared	0.607	0.611	0.555	0.369

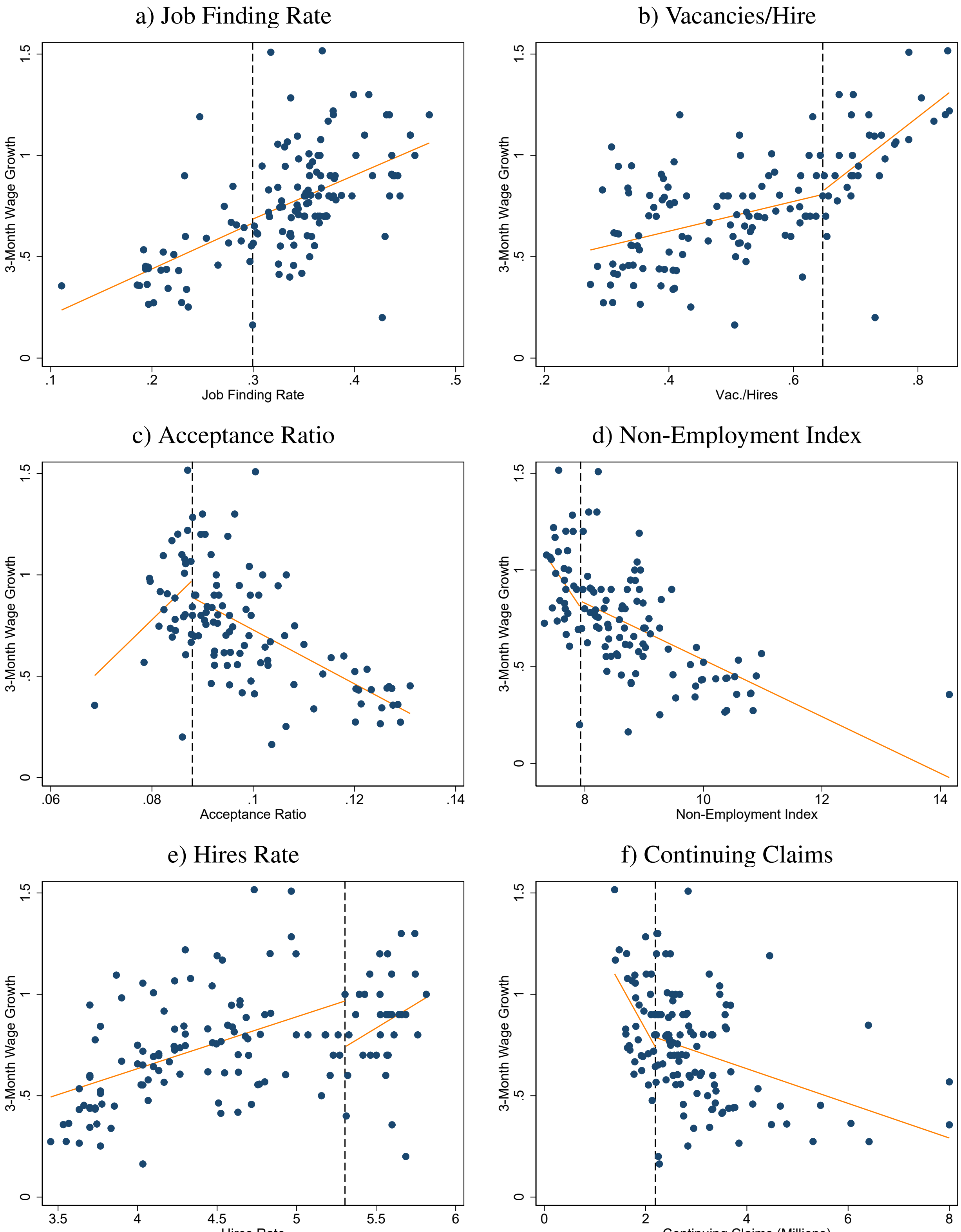
Notes: Panel 1 reports results from regression (7) of 3-month wage changes from the ECI on tightness measures: $\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t$, where the tightness measures are detrended linearly as described in the text. Panel 2 reports results from regression (19): $\Pi_t^w = \beta_0 + \beta_1 \mathbb{I}(X_t > \gamma) + \beta_2 X_t + \beta_3 \mathbb{I}(X_t > \gamma) \cdot X_t + \epsilon_t$ with detrended tightness measures. Panel 3 reports results from regression (20): $\Pi_t^w = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \epsilon_t$ with detrended tightness measures. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Figure A.7: Nonlinearity in the Tightness - Wage Growth Relationship



Notes: Figures show scatterplots of 3-month wage changes from the ECI for the period 1990:q2-2024:q4 against tightness measures. Each dot indicates a quarterly observation. Dashed vertical lines denote the selected break point of the relationship, which is chosen as the 25th percentile in variables that comove negatively with wage growth and the 75th percentile in variables that comove positively with wage growth. Orange lines indicate the best linear fit to the left and to the right of the break point.

Figure A.8: Nonlinearity in the Tightness - Wage Growth Relationship



Notes: Figures show scatterplots of 3-month wage changes from the ECI for the period 1990:q2-2024:q4 against tightness measures. Each dot indicates a quarterly observation. Dashed vertical lines denote the selected break point of the relationship, which is chosen as the 25th percentile in variables that comove negatively with wage growth and the 75th percentile in variables that comove positively with wage growth. Orange lines indicate the best linear fit to the left and to the right of the break point.

F.2 Reconciling Nonlinearity Results for V/ES and Unemployment

If there is a nonlinear relationship between a tightness measure like V/ES, hence θ, and the unemployment rate, then a linear relationship between θ and wage inflation Π^w implies a *nonlinear* relationship between unemployment and Π^w:

Proposition F.1. *Let Π^w be a linear function of tightness θ, i.e., $\Pi^w = \beta \times \theta$ with the constant $\beta > 0$. Let u be a nonlinear function of θ, $u = g(\theta)$, where g is twice differentiable, strictly decreasing, and strictly convex on the interval $\theta \in [0, \infty)$: i.e., $g' < 0$ and $g'' > 0$. Let the range of u on $\theta \in [0, \infty)$ be $u \in [0, 1)$. Then it follows that Π^w is a strictly decreasing, strictly convex function of u on $u \in [0, 1)$.*

Proof. The proof has three steps:

- Since $g(\theta)$ is strictly decreasing on $\theta \in [0, \infty)$, there exists an inverse function denoted $g^{-1}(u)$ which is also strictly decreasing on $u \in [0, 1)$.
- Since $g(\theta)$ is a strictly decreasing, strictly convex function on $\theta \in [0, \infty)$, it follows that its inverse is also a strictly decreasing, strictly convex function on $u \in [0, 1)$.
- We can thus write $\Pi^w = \beta \times g^{-1}(u)$. Since $\beta > 0$, this is also a strictly decreasing, strictly convex function on on $u \in [0, 1)$.

□

The assumption that g is strictly decreasing and strictly convex is quite natural. Consider the steady state relationship between u and θ, which is often assumed to well-approximate the dynamic relationship because unemployment adjusts quickly to its steady state value in practice. To fix ideas, consider the steady state relationship in Bloesch, Lee, and Weber (2025): letting the job finding rate be given by the function $f(\theta)$ and the separation rate into unemployment be denoted $S_u > 0$ (a constant in their benchmark model), this steady state relationship is defined by

$$S_u \times (1 - U) = f(\theta) \times U$$

which requires EU flows to equal UE flows.[14] Rearranging yields

$$U = \frac{1}{1 + \frac{f(\theta)}{S_u}}$$

which is strictly decreasing and strictly convex provided that $f'(\theta) > 0$, which follows from standard assumptions on the matching function.

G CPI

In this section, we expand on the price regressions by providing more detail on the univariate regressions and the bivariate regressions. Table A.22 presents the results from running equation (12) with all variables, each normalized to have mean zero and standard deviation of one. As before, the variables in the table are ordered by their R-squared. These results underlie Table 6 in the main text. We find that V/ES-AHR, V/ES-S, HPW, and the quits rate are also strongly correlated with core CPI inflation. The measures of vacancies per searcher have the greatest fit, followed by HPW, the ratio of vacancies per hire, and the quits rate.

Table A.23 shows the results of the bivariate regression, which includes the quits rate and one other tightness measure. As for wage growth, the combination of the quits rate and vacancies per effective searcher provides the greatest fit. However, in contrast to the wage regressions, the coefficient on the quits rate becomes insignificant in the regressions including vacancies per effective searcher. In all other regressions, the quits rate is significant.

Figure A.9 presents scatterplots of quarterly changes in the core CPI against key tightness measures and confirms that the relationship between tightness and *price* inflation appears to be nonlinear. Each dot indicates an observation of quarterly core CPI changes and tightness. As in the main text, we add dashed vertical lines at the 25th percentile for variables that comove negatively with wage growth and at the 75th percentile for variables that comove positively with

[14] Since there are a unit measure of workers, and workers can only be employed or unemployed, we have total employed workers equals $1 - U$.

wage growth. We plot the fit lines from a linear regression to the left and to the right of these lines. Consistent with the literature on non-linearities in the *price* Phillips curve, we find evidence for a steeper relationship between price inflation and tightness when the labor market is very tight (Cerrato and Gitti, 2022; Crust et al., 2023; Gitti, 2024; Benigno and Eggertsson, 2024).

Table A.22: Contemporaneous Price Inflation Regressions with Tightness Measures

Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) HPW	(4) Vacancy/Hire	(5) Quits Rate
Y = Wage Growth	0.222***	0.221***	0.208***	0.184***	0.175***
	(0.037)	(0.037)	(0.049)	(0.046)	(0.047)
Observations	124	124	124	139	139
R-squared	0.552	0.544	0.485	0.335	0.302

Indep. Var.	(6) NFIB Difficulty Hiring	(7) Aggregate Hours Gap	(8) V/U	(9) Non-Employment Index	(10) Jobs-Workers Gap
Y = Wage Growth	0.161***	-0.158***	0.163***	-0.147***	0.149***
	(0.052)	(0.038)	(0.048)	(0.036)	(0.051)
Observations	127	124	139	124	139
R-squared	0.294	0.278	0.262	0.242	0.221

Indep. Var.	(11) Job Finding Rate	(12) Unemployment	(13) Continuing Claims	(14) CB Jobs Availability	(15) Acceptance Rate
Y = Wage Growth	0.136***	-0.111***	-0.106***	0.103*	-0.091**
	(0.040)	(0.040)	(0.040)	(0.059)	(0.042)
Observations	139	139	139	139	117
R-squared	0.182	0.122	0.111	0.104	0.089

Indep. Var.	(16) Hires Rate	(17) Separation Rate
Y = Wage Growth	0.090**	0.009
	(0.039)	(0.076)
Observations	139	139
R-squared	0.079	0.001

Notes: Table shows results from regression (12) of 3-month price changes from the core CPI on tightness measures: $\Pi_t^p = \beta_0 + \beta_1 X_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A.23: Bivariate Price Inflation Regressions with Tightness Measures

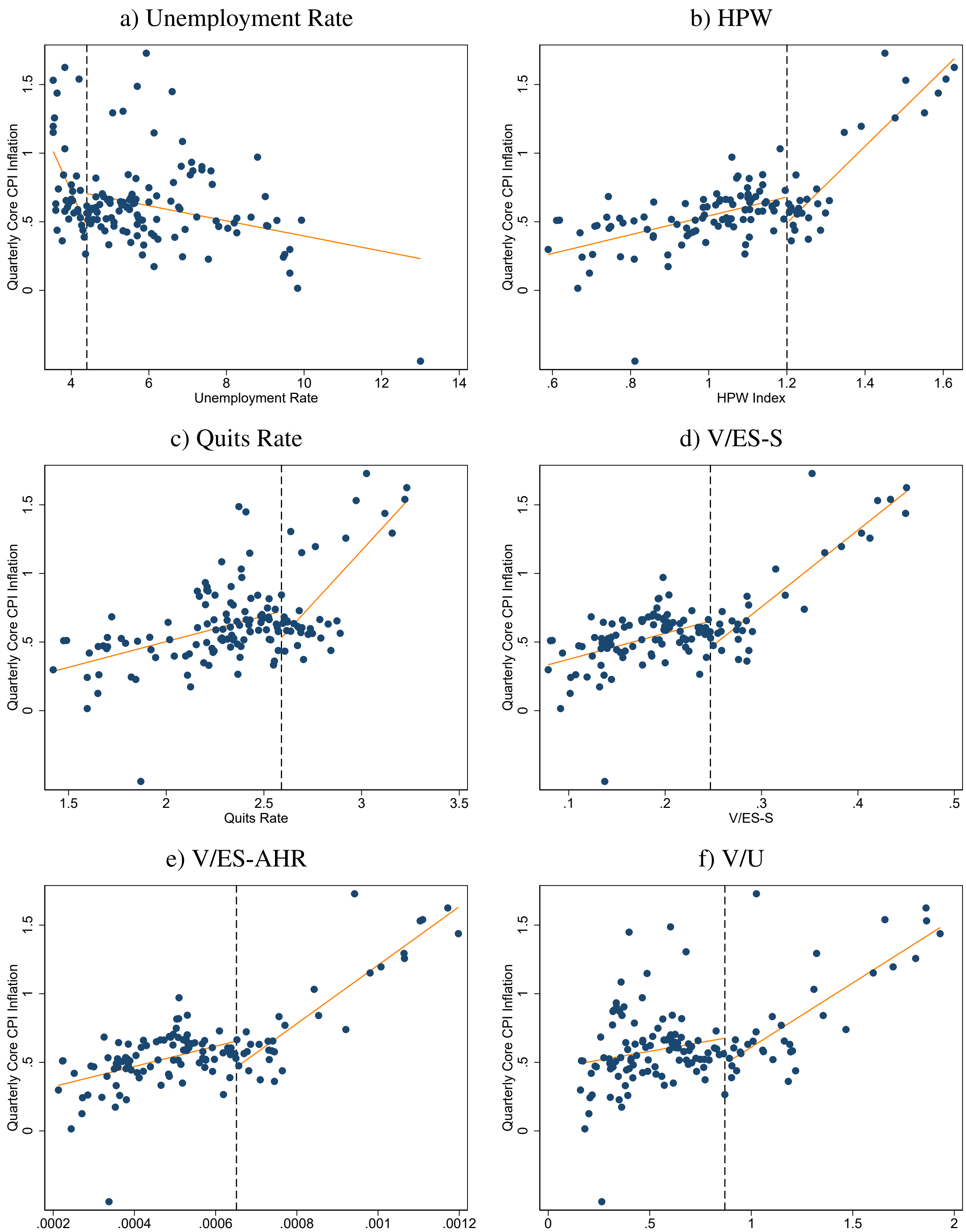
Indep. Var.	(1) V/ES-AHR	(2) V/ES-S	(3) Acceptance Rate	(4) Agg. Hours Gap	(5) Non-Employment Index
Y = Wage Growth	0.212***	0.207***	0.127**	-0.024	-0.017
	(0.050)	(0.051)	(0.055)	(0.076)	(0.067)
Quits Rate	0.012	0.015	0.265***	0.158*	0.164**
	(0.037)	(0.039)	(0.071)	(0.087)	(0.077)
Observations	124	124	117	124	124
R-squared	0.552	0.545	0.455	0.389	0.388

Indep. Var.	(6) NFIB Difficulty Hiring	(7) CB Jobs Availability	(8) Vacancy/Hire	(9) V/U	(10) Unemployment
Y = Wage Growth	0.034	-0.167**	0.121***	0.071	0.072
	(0.049)	(0.067)	(0.033)	(0.067)	(0.084)
Quits Rate	0.149**	0.317***	0.085**	0.121**	0.231***
	(0.057)	(0.074)	(0.035)	(0.053)	(0.080)
Observations	127	139	139	139	139
R-squared	0.385	0.379	0.367	0.323	0.321

Indep. Var.	(11) Separation Rate	(12) Hires Rate	(13) Continuing Claims	(14) Job Finding Rate	(15) Jobs-Workers Gap
Y = Wage Growth	0.033	-0.036	-0.007	0.003	0.000
	(0.060)	(0.067)	(0.038)	(0.100)	(0.079)
Quits Rate	0.179***	0.197***	0.171***	0.172*	0.175**
	(0.049)	(0.071)	(0.053)	(0.104)	(0.076)
Observations	139	139	139	139	139
R-squared	0.313	0.310	0.303	0.302	0.302

Notes: Table shows results from regression (12) of 3-month price changes from the core CPI on tightness measures and the quits rate:: $\Pi_t^p = \beta_0 + \beta_1 X_t + \beta_2 Q_t + \epsilon_t$. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. All measures of tightness are ordered by their fit (R^2). Estimates use data from 1990:q2–2024:q4, 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. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Figure A.9: Nonlinearity in the Tightness - Price Inflation Relationship



Notes: Figures show scatterplots of quarterly changes in core CPI inflation for the period 1990:q2-2024:q4 against tightness measures. Each dot indicates a quarterly observation. Dashed vertical lines denote the selected break point of the relationship, which is chosen as the 25th percentile in variables that comove negatively with wage growth and the 75th percentile in variables that comove positively with wage growth. Orange lines indicate the best linear fit to the left and to the right of the break point.