STAFF REPORTS

NO. 1128
OCTOBER 2024

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FEDERAL RESERVE BANK of NEW YORK

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Federal Reserve Bank of New York Staff Reports, no. 1128
October 2024
https://doi.org/10.59576/sr.1128

Abstract

Good measures of labor market tightness are essential to predict wage inflation and to calibrate monetary policy. This paper highlights the importance of two measures of labor market tightness in determining wage growth: the quits rate and vacancies per effective searcher (V/ES)—where searchers include both employed and non-employed job seekers. Amongst a broad set of indicators of labor market tightness, we find that these two measures are independently the most strongly correlated with wage inflation and also predict wage growth well in out-of-sample forecasting exercises. Conversely, transitory shocks to productivity have little impact on wage growth. Finally, we find little evidence of a nonlinearity in the relationship between wage growth and labor market tightness. These results are generally consistent with the predictions of a New Keynesian DSGE model where firms have the power to set wages and workers search on the job (Bloesch, Lee, and Weber, 2024).

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

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1 Introduction

The evolution of U.S. wage growth has been an object of considerable interest for policymakers in the recent high-inflation environment. Wage growth exhibits cyclical patterns, and this was especially true during COVID and the recovery period: the 12-month change in average nominal hourly earnings surged to 5.9 percent in March 2022, before falling back to 3.6 percent in July 2024. However, standard measures of labor market tightness—such as the unemployment rate or the vacancy-to-unemployment (V/U) ratio—have had a mixed performance in tracking wage growth recently. For example, as panel a of Figure 1 shows, the evolution of unemployment in the COVID period suggested weaker wage growth than was recently observed. Developing good trackers of labor market tightness to predict the path of wage inflation thus remains an important task to calibrate the appropriate stance of monetary policy.

In this paper, we provide an empirical analysis of measures of labor market tightness that is guided by insights from a tractable New Keynesian DSGE model that incorporates a frictional labor market where firms set wages and workers search on the job, developed in Bloesch, Lee, and Weber (2024). Those authors show that once the model is calibrated to U.S. data, tightness is well-summarized either by the quits rate or vacancies per effective searcher (which includes on-the-job searchers in addition to the unemployed), rather than the unemployment rate.[1] The model also predicts that transitory shocks to labor productivity or Total Factor Productivity (TFP) have ambiguous effects on nominal wage growth, depending on various features of the economy such as the specification of monetary policy or firms' price setting power.[2]

We test these predictions empirically in U.S. data using simple econometric methods. As predicted by the model, vacancies over effective searchers and the quits rate closely track wage growth. Together, these two variables explain nearly two thirds of wage growth since 1990 and 78 percent since the onset of COVID in 2020:q2 (through 2024:q2, as of this writing). Other widely used, alternative indicators of labor market conditions are also correlated with wage growth, but less strongly. The effect on wages of transitory productivity shocks (Fernald et al., 2012) is negligible, consistent with the model, where the sign of the effect on wages ambiguous.

These findings reflect the results of simple ordinary-least-squares (OLS) regression estimates of the wage Phillips curve (or wage PC) derived in Bloesch, Lee, and Weber (2024). We also use local projections (Jordà, 2005) to evaluate the performance of these model-informed measures of labor market tightness in forecasting wage growth. The quits rate and the ratio of vacancies over effective searchers have persistent effects on wage growth. A one standard deviation increase in quits or in

[1] Specifically, conditional on quits or vacancies per effective searcher, changes in the unemployment rate separately affect wage growth by changing the composition of searchers, but in the calibrated model this effect is small.

[2] Persistent or anticipated, permanent productivity shocks unambiguously raise nominal wages in the model. As labor is the only factor of production in the model, there is no distinction between TFP and labor productivity shocks.

the tightness measure in the current quarter raises 3-month ECI wage growth four quarters later by about 0.3p.p. Out-of-sample forecasts of ECI wage growth using quits and tightness predict annualized 3-month wage growth of 3.33 percent in 2024:q3.

Finally, given recent interest in nonlinear effects of labor market tightness on price inflation (e.g., Benigno and Eggertsson, 2024), we also investigate whether there is a nonlinear relationship between labor market tightness and wage inflation. We do not find any evidence of nonlinearities. Indeed, there is nothing unusual in the wage/tightness relationship, either during the period of extreme tightness in the aftermath of COVID, or later.

Related Literature. Since its original empirical formulation by Phillips (1958), many authors have estimated relationships between wage growth and labor market tightness. Empirically, we are similar to Galí (2011) and Bloesch, Lee, and Weber (2024) who each provide empirical support for a novel, microfounded wage Phillips curve (wage PC) using OLS regressions in U.S. data: Galí (2011) provides foundations for a wage PC with unemployment as the forcing variable, while Bloesch, Lee, and Weber (2024) do the same but for a wage PC with quits and unemployment, showing that unemployment plays a minimal role in determining wage growth both in their model and in U.S. data. In this paper, we compare the two key measures from their model—quits, and vacancies per effective searcher, which are predicted to be tightly related—against a broad range of other commonly used indicators and also study their out-of-sample forecasting performance. Thus, our approach is most similar to Barnichon and Shapiro (2024), who study OLS estimates of the *price* Phillips curve in U.S. data (see their Table 1) 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 these exercises for U.S. *wage* inflation.

Relative to recent work specifically demonstrating the strong empirical relationship between quits, or job-to-job transitions, and wage growth (e.g., Faberman and Justiniano, 2015; Moscarini and Postel-Vinay, 2017; Barnichon and Shapiro, 2022; Bloesch et al., 2024), we investigate the relationship of wage growth with a broader range of labor market tightness indicators in a "horse race" with quits and vacancies per effective searcher, as well as Total Factor Productivity (TFP) shocks. We also investigate the presence of nonlinearities in the *wage* Phillips curve, finding little evidence on nonlinearities in contrast to related work arguing for a nonlinear relationship between labor market tightness and inflation in the *price* Phillips curve (e.g., Benigno and Eggertsson, 2024).

As a final note, we acknowledge that we use the model of Bloesch, Lee, and Weber (2024) largely for 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., Moscarini and Postel-Vinay, 2023). However, the microfoundations in Bloesch, Lee, and Weber (2024) admit a simple representation of the wage PC similar to what has been used in applied work for estimating the wage PC in terms of unemployment (e.g., Phillips, 1958; Galí, 2011) or other measures of labor market tightness (e.g., Barnichon and Shapiro, 2022). It also admits a two-period, AD-AS representation that clarifies the minimal role of *transitory* productivity shocks on nominal wages, which we test in the data as well.

Roadmap. Section 2.2 briefly describes the model developed by Bloesch, Lee, and Weber (2024) that we use to inform our regression estimates, as well a presenting stylized facts on wage growth and the U.S. labor market. Section 3 analyzes the correlation of wage growth with the labor market variables suggested by the model, comparing them to other, widely used measures of labor market tightness. We also evaluate the response of wage growth to productivity growth, which plays an ambiguous role in the model, and investigate the presence of nonlinearities in the wage Phillips curve. Section 4 studies two applications: first, we develop a measure that tracks wage inflation using as inputs quits and V/ES. We show how this performs in our sample. We then study how our model performs out-of-sample forecasting exercises with local projections. Finally, Section 5 concludes, proposing a new indicator of labor market tightness, which is a composite measure (i.e., weighted average) of quits and vacancies per effective searcher. This reflects the fact that while in the model, either of these measures is sufficient, in practice they may be measured with error, and thus including both as one indicator yields some additional explanatory power for wages in practice. Our proposed indicator is thus a composite, where the weights on these two variables are equal to their weights in a simple OLS regression of wage growth on quits and vacancies per effective searcher. We show that this improves fit in the paper's final table.

2 Theoretical Framework

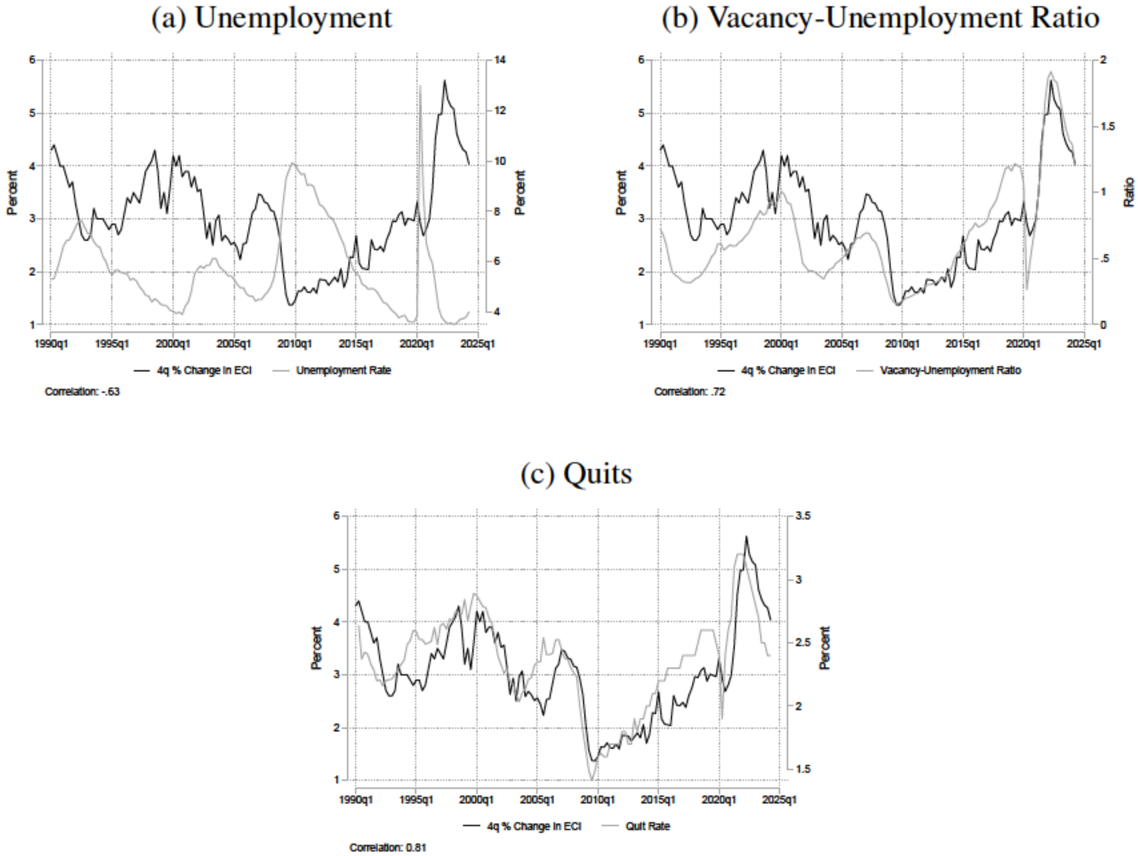
Theoretical frameworks used by both academics and policymakers have been developed to predict nominal wage growth. We first describe several commonly used models. We then describe a new model with on-the-job search and firm wage setting by Bloesch, Lee, and Weber (2024).

2.1 Commonly Used Models to Understand Wage Growth

In a standard Phillips curve framework, inflation is linked to economic tightness, which is captured in the model by the change in marginal costs. Figure 1 shows three measures of economic tightness and their relationship to nominal wage growth.

A standard measure of economic slack is the unemployment rate. Panel (a) of Figure 1 shows the time series of the 12-month ECI growth against the unemployment rate since 1990. The two

Figure 1: Wage Growth versus Labor Market Conditions



Notes: Wage growth is measured as the 12-month change in the ECI. Unemployment is from the BLS. Vacancies are obtained from JOLTS for 2001:q1-2024:q2. We use the composite Help Wanted Index constructed by Barnichon (2010) to obtain vacancies for 1990:q2-2000:q4. Quits rate for private sector workers is from JOLTS for 2001:q1-2024:q2 and from the data by Davis et al. (2012) for 1990:q2-2000:q4.

series are highly negatively correlated (correlation: -0.63). Wage growth is high when unemployment is low in the late 1990s and before the onset of the Great Recession, and drops sharply at the beginning of the early 2000s recession and in the Great Recession. However, the correlation is far from perfect, particularly in the recent period. In fact, the correlation between unemployment and wage growth has been only -0.33 since 2015.

In panels (b) and (c) of Figure 1, we plot two alternative measures of labor market conditions: the vacancy-to-unemployment (V/U) ratio and the quits rate. These two variables are tightly linked to wages in two key types of macro labor models: the models that build on the Diamond-Mortensen-Pissarides (DMP) framework (e.g., Mortensen and Pissarides, 1999) and models with wage posting building on Burdett and Mortensen (1998).[3] In the DMP framework, the ratio of vacancies (V) to unemployment (U), rather than unemployment itself, determines wages. Consistent

[3]Since these models do not contain prices, nominal and real wages have a one-to-one relationship in the models.

with this model, panel (b) shows that the V/U ratio is strongly positively correlated with wage growth (correlation: 0.72). It performs much better than unemployment in predicting wages in the recent period, as it spiked at the same time as wage growth increased significantly.

In on-the-job search models such as Burdett and Mortensen (1998), real wage growth is tightly linked to job-to-job transitions. Wage growth is therefore affected by the employed workers, which constitute a much larger pool of workers than the unemployed. 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. In panel (c), we plot the quits rate for private workers against wage growth and show that the two are strongly correlated (correlation: 0.81).

To shed more light on the mechanisms that link unemployment, tightness, and quits to wages, we next briefly describe a theoretical framework developed by Bloesch, Lee, and Weber (2024). The macro labor models described above do not contain prices and are therefore mostly informative about real wages. They are also steady state models and therefore do not allow for wage dynamics. Conversely, standard New Keynesian DSGE models allow for wage dynamics and give rise to a wage Phillips curve, but do not generally incorporate on-the-job search and are therefore silent about the connection between quits and nominal wage inflation.[4] We build on the recent framework by Bloesch, Lee, and Weber (2024), a DSGE model with wage setting and on-the-job search, which allows us to study the effects of quits, vacancies, and unemployment on wage inflation in a unified model.[5]

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

Our theoretical framework starts with the message that currently employed workers are a central input into the nature of wage dynamics. Bloesch, Lee, and Weber (2024) develop a DSGE model in which employers recruit both from the unemployed and from the employed in other firms. Workers search in a frictional labor market when unemployed and on the job when employed. Firms use wages and vacancies as two alternative tools to attract and retain workers. On the one hand, posting more vacancies allows a firm to increase the likelihood of meeting a worker and of forming a match. On the other hand, 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 job offers. See Bloesch, Lee, and Weber (2024) for details.

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 V/U, labor market tightness is $\theta_t \equiv \frac{V_t}{S_t}$: vacancies V_t divided by the mass of active searchers,

[4] For a recent exception, see, e.g., Moscarini and Postel-Vinay (2023). We use the model in Bloesch, Lee, and Weber (2024) largely for tractability as discussed in the introduction.

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

$\mathcal{S}_t = \lambda_{EE} N_{t-1} + U_{t-1}$, where N_{t-1} is the mass of employed workers entering period t, U_{t-1} is the mass of unemployed, and λ_{EE} is the employed workers' search intensity. Since there are many more employed workers than unemployed in the U.S. economy, most job searchers are employed even though $\lambda_{EE} < 1$.

Using the firms' first-order conditions for vacancies and wages, Bloesch, Lee, and Weber (2024) show that up to a first order we can write the wage Phillips curve as:[6]

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

where the "check" ($\check{x}$) variables denote log deviations from steady state. The appearance of θ_t, rather than V/U, in the wage Phillips curve reflects the presence of on-the-job searchers: intuitively, since unemployed workers are not the only job searchers, labor market tightness is not V/U but $\theta \equiv V/\mathcal{S}$. In the model, when θ_t is high, workers are harder to both recruit and retain, putting pressure on firms to raise wages (i.e., $\beta_\theta > 0$).

The appearance of unemployment U_{t-1} in equation (1), in addition to θ_t, reflects the fact that the *composition* of searchers also 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, the calibrated model predicts that this effect is small ($\beta_U \approx 0$): 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.[7]

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

$$\check{\Pi}^w_t = \beta_Q \check{Q}_t + \beta_U \check{U}_{t-1} + \frac{1}{1+\rho}\check{\Pi}^w_{t+1}. \tag{2}$$

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. However, Bloesch, Lee, and Weber (2024) find that $|\beta_Q| > |\beta_U|$ both in the calibrated model and in reduced-form OLS regressions on U.S. data.

[6] There is an additional term in the wage Phillips curve, omitted here, reflecting the real wage in the previous period. We omit this term since its coefficient is small in the calibrated model and in the data.

[7] The sign of β_U also depends on how vacancy posting costs are specified. In Bloesch, Lee, and Weber (2024) the benchmark specification features vacancy posting costs convex in $\frac{V}{N}$, so that when U is low, firms are larger (N is big), making hiring via vacancies easier, implying *downward* pressure on wages. This yields a slightly positive β_U; assuming a cost function which is linear in V yields a slightly negative β_U.

Hence wage inflation appears more responsive to quits than unemployment.

The wage Phillips curve above does not directly contain an effect of productivity on wages, although the model contains standard productivity shocks which raise firms' output per worker. Productivity shocks only affect nominal wage inflation through their effect on labor market tightness, but do not have independent effects on wage inflation. We discuss the general equilibrium effects of productivity shocks on wages in the model further in Section 3.3 below.[8]

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 (1) or (2) 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 labor market growth, and that V/U should perform worse than a measure of V over all job searchers (i.e. $V/\mathcal{S}$). In the next section, we will examine empirically the correlation of wage growth with these measures.

3 Empirical Determinants of Wage Growth

In this section, we first analyze the correlation of wage growth with the labor market variables suggested by the model. We then examine the relationship between wage growth and other widely-used measures of labor market tightness. We then evaluate the response of wage growth to productivity growth, which plays an ambiguous role in the model.

3.1 Main Variables

The model's wage Phillips curves (1) and (2) imply a tight relationship between wage inflation, tightness (as measured by vacancies over job searchers), quits, and unemployment. To understand their quantitative importance, we run regressions of wage inflation on these variables individually and jointly. 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.[9] Hence, regression coefficients indicate the effects of a one standard deviation increase in the independent variable on wage growth. Our regressions take the form

[8] For a comprehensive analysis of the effects of TFP shocks in the model, see the supplementary online appendix to Bloesch et al. (2024) available on those authors' websites here.

[9] We do not normalize the left-hand side wage growth variable so that each regression coefficient can still be interpreted as percentage point wage growth.

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{3}$$

where Π_t^w is wage inflation measured by the 3-month change in the ECI between quarter $t-1$ and quarter t and X_t is the normalized tightness, quits, or unemployment in quarter t. We use quarterly U.S. data for the period 1990:q2-2024:q2, where the start of the sample is dictated by the availability of data on quits. 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 et al. (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 years in which both are available.

Characterizing the variables in deviations from their mean is consistent with the Phillips curve equations, which express the relationship of the variables in deviations from steady state. We assume that the steady state is equal to a variable's unconditional mean in our sample period. We provide additional robustness checks below, and re-run all our regressions with 12-month changes in the ECI as the left-hand side variable rather than 3-month changes in Appendix B.1.

Our regressions focus on three main independent variables of interest: the unemployment rate, tightness, and quits. We measure tightness as vacancies per *effective* searcher, V/ES, which takes into account the search intensity of different types of workers. The simple model introduced above does not have a nonemployment margin and may therefore miss that workers that are out of the labor force also search for jobs. Following Abraham et al. (2020), we construct the ratio of V/ES to incorporate job search from nonemployment and distinguish between short- and long-term unemployment. Effective searchers are defined as $ES = U_s + 0.48 \cdot U_l + 0.4 \cdot Z^{\text{want}} + 0.09 \cdot Z^{\text{do not want}} + 0.07N$, where U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, Z^{want} is the share of workers not in the labor force that want to work, $Z^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and N is the share of employed workers. The weights on these terms reflect the relative search intensities of these workers estimated by Abraham et al. (2020). We consider V/ES the empirically appropriate measure of labor market tightness.

Columns 1-3 of Table 1 show the results of separately regressing the 3-month ECI wage growth on unemployment, V/ES, and the quits rate. Consistent with the model, the unemployment rate is negatively correlated with wage growth while V/ES and the quits rate are positively correlated with wage growth. A one standard deviation increase in unemployment (by 1.7 percentage points) reduces 3-month wage growth by 0.16 percentage point, while a one standard deviation increase in V/ES (by 0.08) increases wage growth by 0.20 p.p. A one standard deviation increase in quits (by 0.38) is associated with an increase in 3-month wage growth of 0.20 p.p. The R-squared

Table 1: Wage Growth Regressions with Labor Market Variables from the Model

	(1) Δ% Wage	(2) Δ% Wage	(3) Δ% Wage	(4) Δ% Wage	(5) Δ% Wage	(6) Δ% Wage
Unemployment	-0.158***			-0.062***	0.003	-0.003
	(0.024)			(0.022)	(0.031)	(0.026)
V/ES		0.199***		0.154***		0.078***
		(0.018)		(0.026)		(0.030)
Quits Rate			0.200***		0.203***	0.135***
			(0.015)		(0.029)	(0.034)
Observations	137	122	137	122	137	122
R^2	0.342	0.517	0.551	0.544	0.551	0.600

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

in both the regressions involving V/ES and quits is substantially higher than the R-squared for unemployment, explaining more than half of the variation in wage growth.

Column 4 includes the unemployment rate together with V/ES, mirroring the wage Phillips curve equation (1). Column 5 includes the unemployment rate and quits, as in equation (2). In both regressions, the coefficient on unemployment declines significantly, becoming insignificant in the regression involving the quits rate. In contrast, the coefficients on V/ES and particularly on the quits rate remain strong and significant. The empirical results indicate that once quits are accounted for, unemployment holds very little additional information for wage growth.

In column 6, we consider all variables simultaneously. According to the model, V/ES and the quits rate are directly linked and so there should be no additional information in one indicator given the other. While each of the two variables loses some strength, both remain significant and the R-squared rises to 0.6. Unemployment does not have a significant relationship with wage growth in this regression, and removing it from the regression barely changes the other coefficients or the R-squared. Therefore, quits and effective tightness together can explain nearly two thirds of wage growth over the last three decades. In the COVID era of 2020:q2 onwards, the R-squared rises to 0.78.

3.2 Alternative Measurements of Tightness

We next examine the correlation between wage growth and alternative measures of labor market conditions used in the literature. We start with the standard V/U measure featured in the DMP framework, and then expand to ten additional widely used measures of labor market tightness. While some of these variables do not have a direct correspondence in the model developed above, empirically they provide further information on the strength of the labor market and thus may be relevant for wage growth. Table 2 shows the results from running equation (10) with these alternative variables, each normalized to have mean zero and standard deviation of one. We note

Table 2: Wage Growth Regressions with Alternative Tightness Measures

Indep. Var	(1) V/U	(2) Job Find. Rate	(3) ln Cont. Claims	(4) AC	(5) GS Worker's Gap
Y=Wage Growth	0.172***	0.155***	-0.128***	-0.156***	0.178***
	(0.022)	(0.021)	(0.035)	(0.026)	(0.022)
Observations	137	137	137	115	137
R^2	0.406	0.329	0.223	0.305	0.436
Indep. Var	**(6) Hires Rate**	**(7) Hires/Vac.**	**(8) NFIB Difficulty Hiring**	**(9) CB Jobs Availability**	**(10) Separation Rate**
Y=Wage Growth	0.124***	-0.170***	0.175***	0.170***	0.004
	(0.028)	(0.040)	(0.026)	(0.029)	(0.037)
Observations	137	95	125	137	137
R^2	0.212	0.376	0.408	0.399	0.000

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

that not all of the variables are available for the entire sample period, and thus the number of observations varies. We provide definitions of all the variables in Appendix A.

We find that all labor market indicators, except for the separation rate, are strongly correlated with wage growth. Comparing the results to Table 1, we find that the quits rate and the ratio of vacancies over effective searchers, V/ES, have the greatest standardized coefficients (0.200 and 0.199, respectively) and R-squared coefficients (0.551 and 0.517, respectively). Thus, while each of the alternative indicators provide insights, the model-based measurements provide the most predictive power of wage growth. 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; for example, some coefficients flip signs.

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. Table 3 shows that generally quits holds up as the strongest indicator, and that in most regressions the other indicator becomes insignificant. V/U and the separation rate become weakly significant, but remain overall much weaker than the quits rate. The regression thus suggests that once the quit rate is accounted for, there is little additional information in other indicators of labor market tightness.

We show in Appendix B.1 that the insights hold similarly with 12-month wage changes. In Appendix B.2, we provide additional robustness checks. First, we run the regression with 3-month wage growth between quarter t and $t+1$ as dependent variable to analyze the predictive power of the labor market variables. Second, rather than demeaning the variables we re-run the regression with changes of all variables (including wage growth). We find similar results to before, though the results in differences are considerably noisier. Appendix B.3 performs a similar analysis at

Table 3: Wage Growth Regressions (3-month change) with Alternative Indicators and Quits

Y=Wage Growth	(1) V/U	(2) Job Find. Rate	(3) ln Cont. Claims	(4) AC	(5) GS Worker's Gap
First Indep. Var (X_t)	0.043*	0.006	0.005	0.024	0.019
	(0.0243)	(0.0248)	(0.0223)	(0.0216)	(0.0352)
Quits Rate	0.167***	0.195***	0.204***	0.219***	0.184***
	(0.0229)	(0.0248)	(0.0197)	(0.0226)	(0.0342)
Observations	137	137	137	115	137
R^2	0.561	0.552	0.552	0.598	0.553
Y=Wage Growth	**(6) Hires Rate**	**(7) Hires/Vac.**	**(8) NFIB Difficulty Hiring**	**(9) CB Jobs Availability**	**(10) Separation Rate**
First. Indep. Var (X_t)	-0.005	-0.019	0.007	-0.008	0.026*
	(0.0216)	(0.0297)	(0.0298)	(0.0309)	(0.0152)
Quits Rate	0.203***	0.194***	0.194***	0.207***	0.203***
	(0.0194)	(0.0221)	(0.0287)	(0.0293)	(0.0152)
Observations	137	95	125	137	137
R^2	0.552	0.655	0.574	0.552	0.561

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

the industry level and shows that variation in quits and tightness across industries can explain differences in wage growth.

3.3 Productivity

We next analyze the effect of productivity changes on wage growth. While productivity plays a role in the model, the effect on wage growth is ambiguous. We perform similar national regressions with productivity as in the previous tables, with measures of total factor productivity (TFP) and labor productivity. We obtain 3-month changes in productivity from Fernald et al. (2012), and use three different definitions of productivity as our independent variables. As before, regressions are run for the period 1990:q2-2024:q2.

Table 4: ECI and Productivity

	(1) ECI 3-month Change	(2) ECI 3-month Change	(3) ECI 3-month Change
Labor Productivity 3-month Change	-0.011		
	(0.010)		
TFP 3-month Change		-0.003	
		(0.008)	
TFP 3-month Change (Util. Adj.)			-0.004
			(0.009)
Observations	136	136	136
R^2	0.013	0.001	0.002

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

Table 4 shows that in general, productivity does not show a strong negative or positive effect on wage inflation. This is the case whether productivity is measured as labor productivity, TFP, or utilization-adjusted TFP. While the coefficient is negative in all three cases, it is statistically indistinguishable from zero. Compared to other measures of the labor market, productivity is much weaker at predicting wage growth.

To make sense of this empirical finding, we again turn to the model developed by Bloesch et al. (2024). In a supplementary appendix, those authors study the effects of TFP shocks in a simplified version of the model which admits a two period, Aggregate Demand (AD) and Aggregate Supply (AS) representation.[10] That AD-AS framework makes two points about TFP shocks. First, TFP shocks only affect nominal wage inflation through their effect on labor market tightness, and thus do not have independent predictive power (this can already be seen by the fact that these shocks fail to appear on the right-hand-side of the wage PCs, noted above). Second, positive, *transitory* TFP shocks can either move wage inflation and tightness up, or down: the sign is ambiguous and depends on the responsiveness of monetary policy to price inflation, the amount of market power possessed by firms, etc. Simulated IRFs confirm this prediction in the calibrated, infinite-horizon model of Bloesch et al. (2024), as well as demonstrating that highly *persistent* TFP shocks or anticipated, permanent future TFP generally raise nominal wages unambiguously.[11] We do not test this latter result here, given our focus on the business cycle properties of nominal wage growth.

In Appendix C, we also evaluate the effect of TFP shocks at the industry level empirically and find a modest positive effect of productivity on industry-level wages. This may reflect the fact that unlike in national regressions, which look at the effect of shocks on all firms, industries which receive positive shocks outcompete other industries for workers by raising wages.

3.4 Non-Linearity in the Relationships

Benigno and Eggertsson (2024) point to a potential non-linearity in the relationship between price inflation and V/U. We evaluate non-linearities in wage inflation with our measures of tightness. We first provide scatterplots of the relationship between wage growth and quits or V/ES, and then we run a regression with an indicator for a tight labor market.

Figure 2 presents scatterplots of the quits rate (left panel) and of V/ES (right panel) against 3-month ECI wage growth. We estimate the slope with a local polynomial. For both variables, we do not find a strong non-linearity.

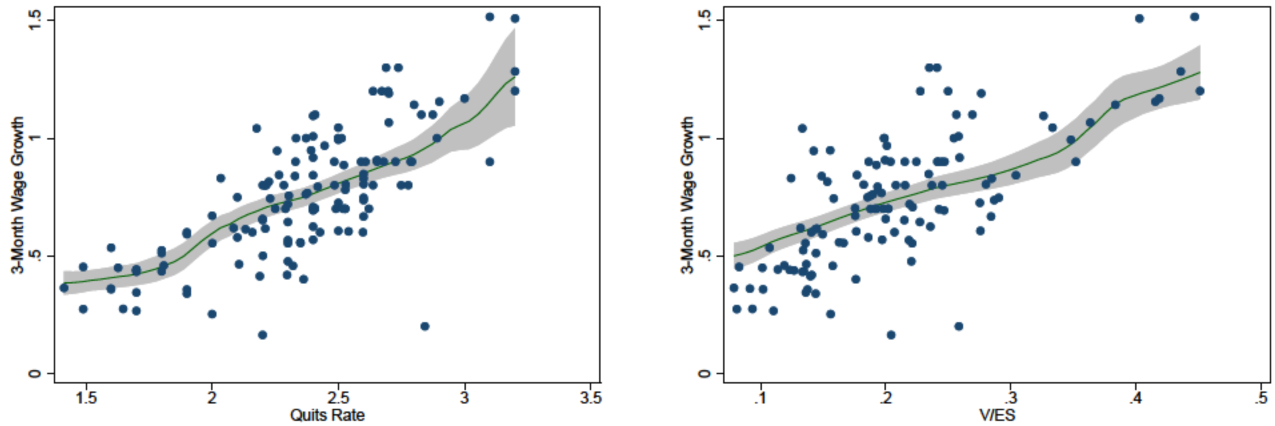
It is possible that in particular for quits there is a slight increase in the slope for high values of the quits rate. To test whether there is a threshold beyond which quits or V/ES have a non-linear

[10] Specifically, see the supplementary online appendix to Bloesch et al. (2024) available on those authors' websites here.

[11] We are grateful to those authors for creating these results for us; they are available upon request.

Figure 2: Wage Growth and V/ES or Quits

(a) Wage Growth and Quits (b) Wage Growth and V/ES



Notes: We plot 3-month wage changes from the ECI on variables for the period 1990:q2-2024:q2 against quits rate and V/ES. Independent variables are not standardized.

impact on wage inflation, we run a threshold regression. We set the threshold to be at the 75th percentile of the distribution (quits rate at 2.6% and V/ES at 0.245) and run

$$\Pi_t^w = \beta_0 + \alpha X_t + \zeta \mathbf{I}\{X_t > 75th \text{ pctile}\} + \beta X_t \times \mathbf{I}\{X_t > 75th \text{ pctile}\} + \epsilon_t, \tag{4}$$

Table 5: Wage Growth Regressions (3-month change) with V/ES and Threshold

	(1) %Δ Wage	(2) %Δ Wage
Quits Rate	0.178*** (0.0155)	
Q Threshold (75 pctile)	-0.0629 (0.0731)	
Q Threshold (75 pctile) × Quits Rate	0.0949 (0.059)	
V/ES		0.256*** (0.0366)
V/ES Threshold (75 pctile)		-0.072 (0.088)
V/ES Threshold (75 pctile) × V/ES		-0.053 (0.055)
Observations	136	122
R^2	0.559	0.531

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

We report the regression results in Table 5. We do not find a significant nonlinear term for both quits and V/ES. Overall, their significance is picked up by the linear term. For quits the interaction term is weakly positive, but it is insignificant.[12]

4 Applications: An Index and Forecasting

This section has two components. Section 4.1 develops an index of wage growth that incorporates the quits rate and V/ES. This index provides good contemporaneous fit with wage growth, especially during the COVID period, and is a useful visual summary of our findings for the quits rate and V/ES. Section 4.2 extends this measure to study future wage growth. We first demonstrate that the current quits rate and V/ES have significant effects on future wage growth. We then construct forecasts for ECI wage growth given the current state of the labor market.

4.1 An Index for Wage Growth

We develop an index for wage growth that takes as inputs the coefficients of a regression of 3-month growth on Quits and V/ES. This takes regressions of the form:

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

where Π_t^w is wage inflation measured by the 3-month change in the ECI between quarter $t-1$ and quarter t and X_t is the labor market variable of interest in quarter t. We run the regression for the period 1990:q2-2024:q2, as dictated by the availability of quits. Table 6 shows the results from running this regression using V/ES and quits separately and jointly.

Table 6: Wage Growth Regressions (contemporaneous) with V/ES and Quits

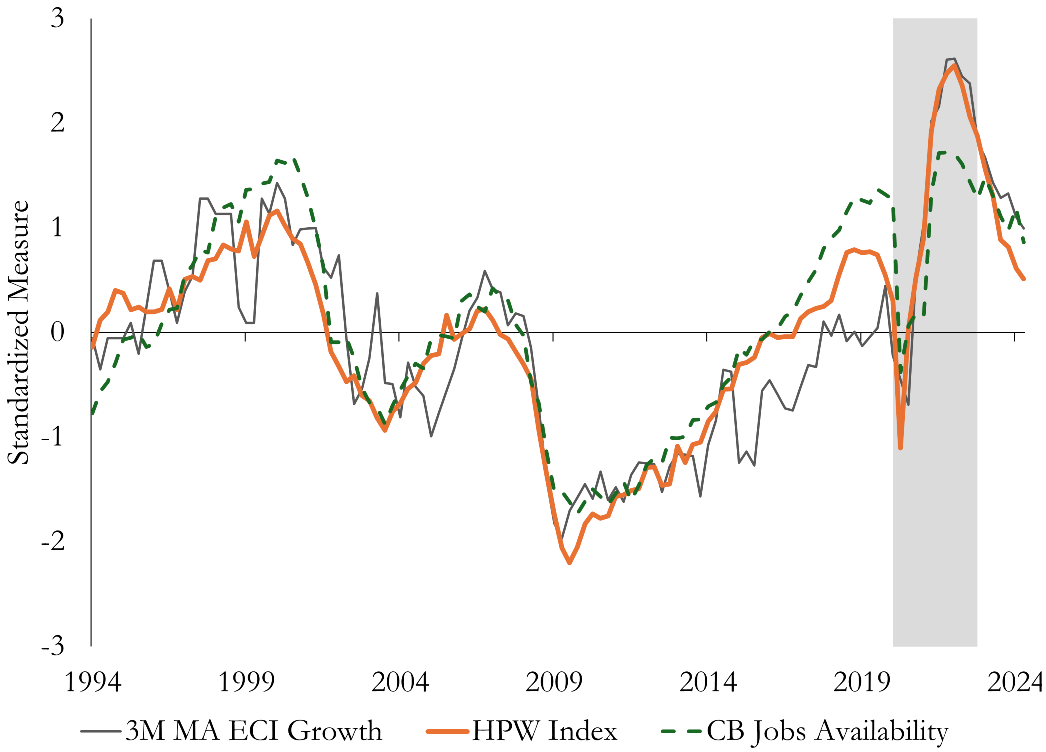
	(1) Δ % Wage	(2) Δ % Wage	(3) Δ % Wage
V/ES	0.199***		0.079***
	(0.014)		(0.027)
Quits Rate		0.200***	0.137***
		(0.014)	(0.026)
Observations	122	137	122
R^2	0.517	0.551	0.600

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

We see the significance of using both the quits rate and V/ES jointly. We take the fitted value from the regression of Column (3) as the predicted wage growth from our two indicators. We refer to this index as the *Heise-Pearce-Weber (HPW) Tightness Index*.

[12] This result also holds when taking a slightly higher cutoff to capture the far right in the graph with quits; there is a positive interaction term but it is insignificant as well for a threshold of the quits rate at the 95th percentile (2.9).

Figure 3: The HPW Index Tracks Wage Growth Well Even During COVID



Notes: The HPW Tightness Index, based on quits and vacancies per searcher, tracks wage growth well even during the COVID pandemic and recovery. All series are normalized to have zero mean and variance of one for ease of comparison. Wage growth is measured using the employment cost index. "CB Jobs Availability" is taken from the Conference Board. Covid period and recovery 2020:Q1—2022:Q4 is shaded.

Figure 3 demonstrates the fit of the HPW Index visually by plotting it against wage growth, measured using a 3-period moving average of the 3-month growth in the ECI (both series are normalized to have a mean of zero and variance of one for ease of comparison). We compare our measure against a common measure of labor market tightness: the Conference Board's survey measure of consumers' perception of job availability.

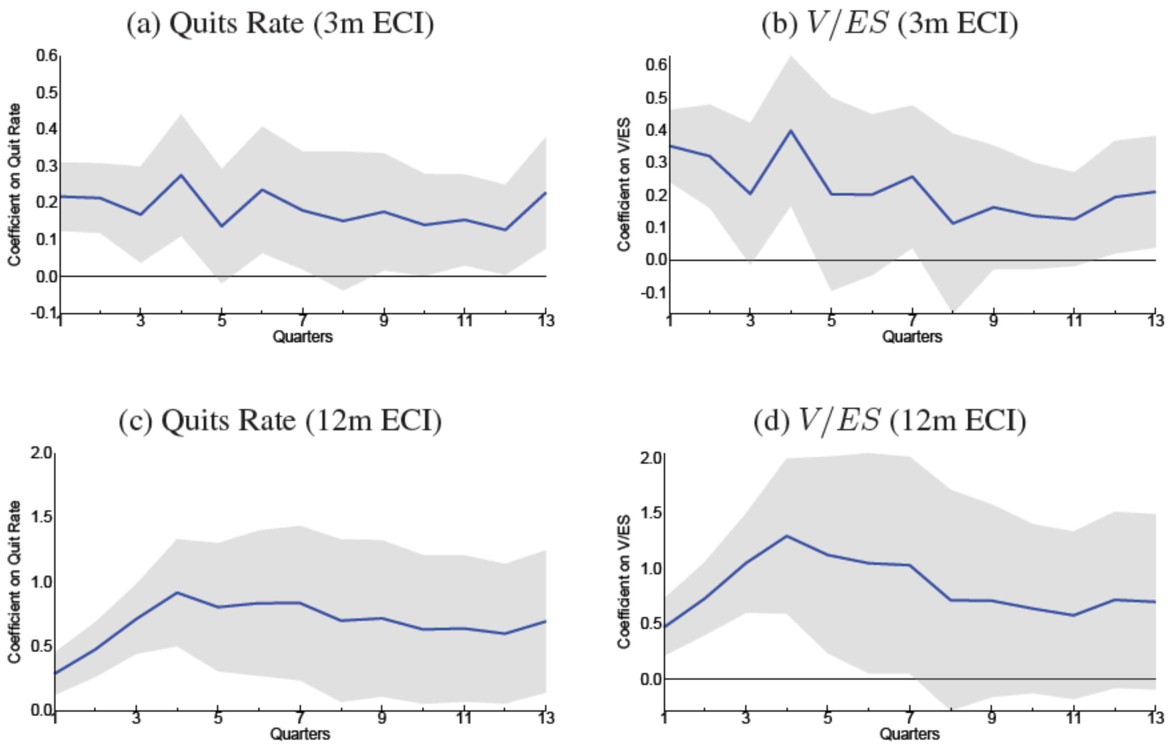
Both the Conference Board measure and the HPW index track wage growth well in the pre-pandemic period. However, in the pandemic period, our measure performs significantly better. Having shown the ability to predict contemporaneous wage growth, we now turn to a forecasting exercise where we leverage the quits rate and V/ES to make predictions on wage growth.

4.2 Forecasting Wage Growth

We estimate a distributed lag model to analyze whether changes in labor market conditions have effects on future wages. We run:

$$\Pi^w_{t+h} = \beta_0 + \beta_h X_{t-1} + \sum_{l=2}^{L} \alpha_{h,l} X_{t-l} + \epsilon_t, \tag{6}$$

Figure 4: Estimated Coefficients of Distributed Lag Regressions of ECI Growth



Notes: Gray area shows 90 percent confidence bands using Newey-West standard errors. Top left panel shows the results from running specification (6) with the quit rate as right-hand side variable, using 3-month ECI wage changes. Right panel shows the results using V/ES with 3-month wage changes. The bottom panels show analogous results using 12-month ECI wage changes.

where Π^w_{t+h} is the 3-month change in the ECI between quarter $t+h-1$ and $t+h$, and X_{t-l} is either the quits rate or the tightness measure V/ES in quarter $t-l$, standardized to have mean zero and standard deviation of one. We include lags up to $L = 4$ to pick up lagged dynamics, and run the regression for $h = 1, ..., 12$ quarters.

The top left panel of Figure 4 shows the resulting estimated coefficients β_h for quits and the top right panel shows the coefficients for tightness. Both sets of coefficients, while noisy, are positive and significant for the first four quarters and for some quarters after that. An increase in the quits rate or tightness by one standard deviation is associated with an increase in 3-month wage growth by about 0.2-0.3 p.p. in the near term. The bottom panels show the results from running the model with 12-month wage growth as the left-hand side variable. The estimated coefficients rise for the first four quarters, peaking at a level of around one.

Overall, the model shows that quits and V/ES are significantly correlated with wage growth for several quarters into the future. This persistent effect arises because quits and tightness are themselves persistent (autocorrelation 0.95 and 0.97, respectively). This feature may generate predictability of wage growth which we investigate next. We generate out-of-sample forecasts of what the reading of the 3-month ECI growth will be in the next quarter (2024:q3). For this purpose, we proceed as follows. First, in the first half of the sample from 1990:q2 to 2005:q4, we run a regression of the form

$$\Pi_t^w = \beta_0 + \beta_1 X_{t-1} + \epsilon_t, \tag{7}$$

where Π_t^w is the 3-month change in the ECI between quarter $t-1$ and t, and X_{t-1} represents a vector containing the quits rate and the tightness measure V/ES in quarter $t-1$. We use both measures of labor market conditions as regressors to maximize predictive power. Note that we do not include further lags X_{t-2}, X_{t-3}, and so on, since the labor market variables are persistent as discussed, and so including further lags holds very little additional information.

We obtain from this step regression estimates $\hat{\beta}_0$ and $\hat{\beta}_1$, which we use together with the observed quits rate and tightness in quarter t, X_t, to generate a predicted value for wage growth in 2006:q1, Π_{t+1}^w. Next, we expand the sample period by one quarter to 1990:q2 to 2006:q1, re-run the regression, obtain updated estimates $\hat{\beta}_0$ and $\hat{\beta}_1$, and construct a forecast for wage growth for 2006:q2. We proceed analogously for all quarters up to 2024:q2. We annualize all wage growth for easier interpretability.

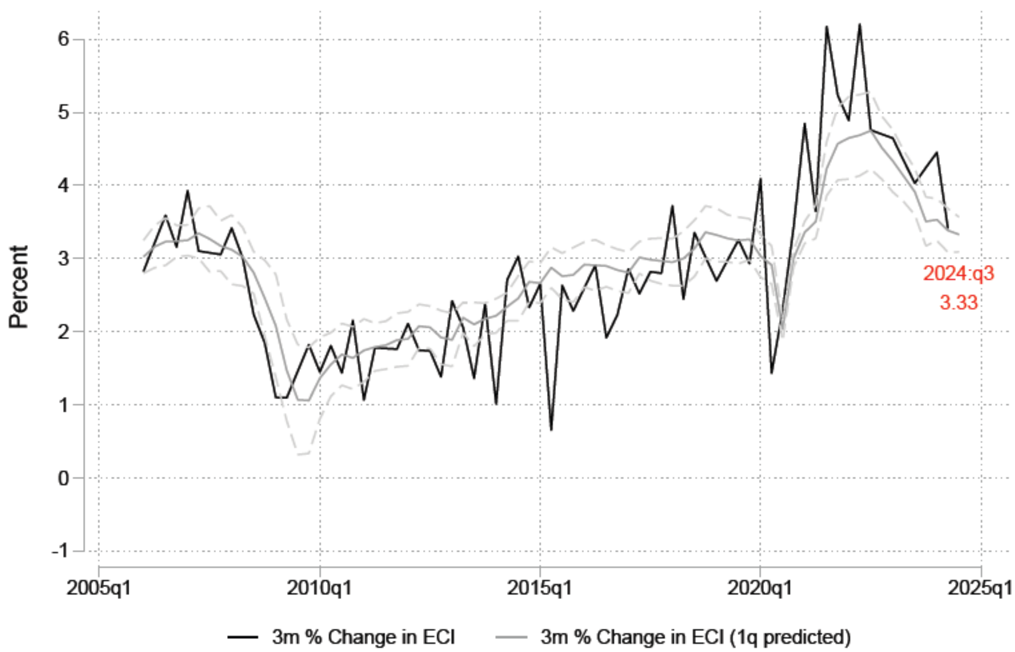
Figure 5 shows the one-quarter ahead forecast of 3-month annualized ECI wage growth over our sample period. Dashed lines are 90 percent confidence intervals. In every quarter, we compare the realized ECI against the predicted ECI for that quarter, using the prediction from one quarter earlier. The approach performs very well during our sample period (correlation with realized wage growth: 0.85). Based on our methodology, we predict an annualized 3-month ECI reading of 3.33 percent in 2024:q3 (0.82 percent compared to the previous quarter), after 3.41 percent annualized in 2024:q2. Our methodology can explain about 85 percent of the increase in wages in 2020:q3 to 2023:q1, and about 90 percent of the decline in wages between 2023:q1 and 2024:q2.

In Appendix B, we present similar predictions using 12-month wage growth as dependent variable. In Appendix D, we alternatively use the standard V/U ratio and analyze its ability to forecast wage growth. We find that the root mean squared error (RMSE) with this alternative approach rises from 0.64 in the baseline to 0.93 with V/U, a 46 percent increase. Thus, V/ES and quits are a better predictor of wage growth than V/U.

5 Conclusion

In this paper, we have shown empirically that good measures of labor market tightness must incorporate the search behavior of the employed. In a broad array of measures of labor market tightness, measures that account for the behavior of the employed do the best independently and jointly in predicting wage growth. Specifically, our analysis shows that quits and vacancies per effective searcher are the most strongly correlated with wage growth. Once these factors are accounted

Figure 5: One-Quarter Ahead Forecasts of Annualized 3-Month ECI Growth



Notes: Figure shows annualized 3-month ECI wage growth (black) against the predicted annualized 3-month wage growth from one quarter earlier (gray). 90 percent confidence bands are dashed in gray.

for, changes in the unemployment rate contain little additional explanatory power for the path of wages in the U.S. economy. We find little role for transitory labor productivity shocks. Our newly constructed HPW tightness index closely tracks wage inflation both pre- and post-COVID and can therefore be a useful tool for policymakers to assess the state of the labor market and to calibrate monetary policy.

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Appendix

A Definition of Labor Market Tightness Variables

The ten additional, widely used labor market tightness indicators discussed in the main text are defined here.

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

- **Continuing claims**: This measure is the number of continuing claims for unemployment insurance, averaged across weeks in the month.

- **Acceptance Ratio (AC)**: 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.

- **Goldman-Sachs (GS) workers' gap**: This measure is defined as (Vacancies – unemployment)/Labor force. A high workers' gap suggests that there are many vacancies compared to unemployed workers and hence the labor market is relatively tight.

- **V/ES** This measure is defined as vacancies / effective searchers, where effective searchers are defined as $ES = U_s + 0.48 \cdot U_l + 0.4 \cdot Z^{\text{want}} + 0.09 \cdot Z^{\text{do not want}} + 0.07N$, where U_s is the share of short-term unemployed, U_l is the share of long-term unemployed, Z^{want} is the share of workers not in the labor force that want to work, $Z^{\text{do not want}}$ is the share of workers not in the labor force that do not want work, and N is the share of employed workers. The weights on these terms reflect the relative search intensities of these workers estimated by Abraham et al. (2020).

- **Hires rate**: This is the ratio of hires to total employment in a given period, computed using JOLTS data.

- **Hires/Vacancies ratio:** This is a measure of the job filling rate for firms, computed as hires divided by job openings from JOLTS. It is higher when the labor market is slack, indicating that firms have an easier time filling their job openings.

- **NFIB:** 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.

- **Conference Board (CB) jobs availability**: 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).

- **Separation rate**: 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) from layoffs (involuntary exit).

B Robustness and Industry Analysis

In the main text, we showed that vacancies per effective searchers and quits are strongly correlated with 3-month nominal wage growth contemporaneously at the national level. In this section, we explore robustness of the main results and examine variation at the industry level. Appendix B.1 re-runs all our regressions using 12-month changes in ECI as dependent variable. Appendix B.2 explores one one-quarter ahead regressions and re-runs the regressions in differences. In Appendix B.3, we run some of our main text regressions at the industry level. We find that the qualitative results in the text hold when leveraging variation across industries and when changing the wage measurement.

B.1 Regressions with 12-Month Wage Changes

In this section, we re-run all our regressions using 12-month changes in ECI as opposed to 3-month changes. Table A. 1 presents the results analogous to our main Table 1 in the main text. The results are similar. Columns 1 and 2 show that a one standard deviation increase in unemployment is associated with a decline in 12-month wage growth by 0.57 p.p., while a one standard deviation increase in the V/ES ratio is associated with an increase in wage growth of 0.74 p.p. Column 6 again includes all regressors jointly. As in the main text, the coefficient on unemployment becomes insignificant in this regression, while the coefficients on V/ES and the quits rate remain significant. The R-squared of the regression is 0.74. The R-squared is the same when the unemployment rate is excluded, highlighting that quits and tightness together explain about three quarters of 12-month wage growth.

Table A. 1: National-Level Wage Growth Regressions (12-Month ECI)

	(1) Δ % Wage	(2) Δ % Wage	(3) Δ % Wage	(4) Δ % Wage	(5) Δ % Wage	(6) Δ % Wage
Unemployment	-0.572***			-0.219*	0.023	-0.013
	(0.133)			(0.122)	(0.130)	(0.120)
V/ES		0.737***		0.577***		0.310*
		(0.075)		(0.109)		(0.181)
Quits Rate			0.732***		0.750***	0.476***
			(0.069)		(0.125)	(0.176)
Observations	137	122	137	122	137	122
R^2	0.405	0.641	0.664	0.671	0.662	0.735

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

We next re-run the wage growth regressions with the alternative, widely used measures of labor market tightness, using 12-month wage changes. The results are presented in Table A. 2.

Table A. 2: Wage Growth Regressions with Alternative Measures (12-Month ECI)

Indep. Var	(1) V/U	(2) Job Find. Rate	(3) ln Cont. Claims	(4) AC	(5) GS Worker's Gap
Y=Wage Growth	0.652***	0.634***	-0.471***	-0.659***	0.648***
	(0.089)	(0.070)	(0.156)	(0.097)	(0.107)
Observations	137	137	137	115	137
R^2	0.526	0.496	0.273	0.484	0.519
Indep. Var	(6) Hires Rate	(7) Hires/Vac.	(8) NFIB Difficulty Hiring	(9) CB Jobs Availability	(10) Separation Rate
Y=Wage Growth	0.485***	-0.593***	0.637***	0.628***	0.065
	(0.109)	(0.176)	(0.110)	(0.124)	(0.155)
Observations	137	95	125	137	137
R^2	0.291	0.370	0.491	0.490	0.005

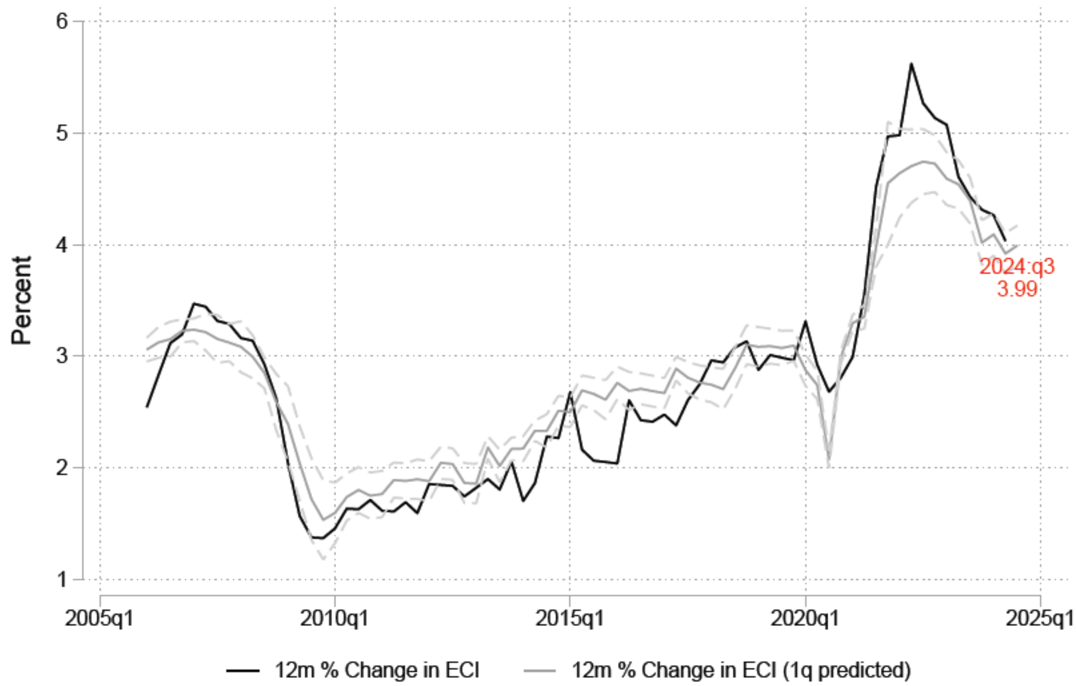
Notes: Table shows results from a regression of 12-month wage changes from the ECI on variables for the period 1990:q2-2024:q2. Independent variables are standardized to have zero mean and standard deviation of one. Newey-West standard errors are included. *, **, and *** denote significance at the 10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

Overall, the results are very similar to those in the main text in terms of relative importance. V/U has the highest R-squared (0.53), but it is still significantly lower than the R-squared for V/ES (0.64) and quits (0.66). Consistent with the main text, each independent variable has significant predictive power except for the separation rate.

Figure A. 1 presents our estimated one-quarter ahead forecast of the 12-month change in the ECI, computed using a similar methodology as in the main text. The only difference to the main text is that we add an additional dummy for the post-COVID period in the regression. Since the constant in the regression reflects an average over the entire period, it does not pick up the level shifts of wage growth in the post-COVID period. As a result, the 12-month wage growth in the post-COVID period is systematically too low. To remedy this issue, we include in the regression a dummy for the post-COVID period, starting in 2021:q2. Including this dummy in the regression shifts the predicted wage growth up in the current period compared to the pre-COVID period.

Overall, the approach performs very well during our sample period (correlation with realized wage growth: 0.97). Based on our methodology, we predict a 12-month ECI reading of 3.99 percent in 2024:q3. Note that the model overstates the drop in wage growth in 2020:q3, at the height of the COVID pandemic, due to the large drop in quits and tightness in the previous quarter. Our model predicts a large negative spike in wage growth following this sudden deterioration in the labor market, which did not materialize in practice.

Figure A. 1: One-Quarter Forecast of 12-Month ECI Growth



Notes: Figure shows annualized 12-month ECI wage growth (black) against the predicted 12-month wage growth from one quarter earlier (gray). 90 percent confidence bands are included.

B.2 Further Robustness

To show the predictive power of our main variables of interest, we regress the 3-month forward change in the ECI between quarter t and $t+1$ on all variables to show that the qualitative messages of Section 3 still hold. We mirror the structure of the main text with Tables 1 and 2. The only difference is that we focus on a quarter ahead instead of contemporaneous prediction.

Table A. 3 reports the results for the variables from the model. The results are similar to the ones using contemporaneous wage growth in the main text. Note that the effect of quits is still the strongest predictor of wage growth the next period, both in the magnitude of the coefficient and in terms of the R-squared. The magnitudes are similar to the ones in the main text. Quits has even stronger R-squared for the next period than contemporaneously, with R-squared equal to 0.58. This has implications for forecasting, which was discussed in Section 4.

We next discuss measuring our main variables in changes rather than levels. In our framework in the main text, we assume that the unconditional mean of each variable is the steady state as we de-meaned and standardized each variable. In this exercise, we compute each variable in changes, which may provide a similar measure of deviation. We compute the four-quarter change of all

Table A. 3: Wage Growth Regressions One Quarter Ahead

	(1) Δ % Wage	(2) Δ % Wage	(3) Δ % Wage	(4) Δ % Wage	(5) Δ % Wage	(6) Δ % Wage
Unemployment	-0.139***			-0.025	0.0643**	0.066***
	(0.023)			(0.023)	(0.022)	(0.019)
V/ES		0.196***		0.178***		0.061**
		(0.015)		(0.025)		(0.025)
Quits Rate			0.203***		0.255***	0.207***
			(0.014)		(0.021)	(0.030)
Observations	136	121	136	121	136	121
R^2	0.271	0.502	0.581	0.506	0.603	0.636

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

Table A. 4: Wage Growth Regressions One Quarter Ahead

Indep. Var	(1) V/U	(2) Job Find. Rate	(3) ln Cont. Claims	(4) AC	(5) GS Worker's Gap
Y=Wage Growth	0.165***	0.152***	-0.108***	-0.158***	0.168***
	(0.018)	(0.018)	(0.033)	(0.020)	(0.018)
Observations	136	136	136	114	136
R^2	0.378	0.314	0.164	0.314	0.396
Indep. Var	(6) Hires Rate	(7) Hires/Vac.	(8) NFIB Difficulty Hiring	(9) CB Jobs Availability	(10) Separation Rate
Y=Wage Growth	0.131***	-0.171***	0.173***	0.168***	-0.026
	(0.020)	(0.028)	(0.020)	(0.021)	(0.028)
Observations	136	94	124	136	136
R^2	0.237	0.372	0.395	0.396	0.009

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

variables included in our list of widely-used labor market tightness indicators, including 3-month wage growth (ECI). Taking the change of wage growth as well is consistent with the Phillips curve equation (1) since the left-hand side is the deviation in wage growth from steady state. Table A. 5 reports the results for the variables in the model and Table A. 6 reports the results for the remaining alternative labor market tightness variables.

These regressions are broadly consistent with the main message of the text, though the coefficients on some measures are noisier and less significant. The R-squared coefficients also drop significantly compared to before. Importantly, when the quits rate changes are included with changes in vacancy per effective searcher, changes in the quits rate loses its significance. It is thus likely that for analysis purposes, the *level* of the quits rate, and its deviation from the long-run trend, may be a better predictor of wage growth.

Table A. 5: National-Level Wage Growth Regressions (Four Quarter *Change* in Variables)

	(1) Δ QoQ Change	(2) Δ QoQ Change	(3) Δ QoQ Change	(4) Δ QoQ Change	(5) Δ QoQ Change	(6) Δ QoQ Change
Unemployment	-0.122***			-0.004	-0.041	-0.000
	(0.030)			(0.024)	(0.023)	(0.020)
V/ES		0.218***		0.214***		0.168**
		(0.024)		(0.037)		(0.062)
Quits Rate			0.184***		0.145***	0.051
			(0.025)		(0.037)	(0.059)
Observations	134	118	133	118	133	118
R^2	0.159	0.259	0.214	0.259	0.221	0.263

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

Table A. 6: National-Level Wage Growth Regressions (Four Quarter *Change* in Variables)

Indep. Var	(1) V/U	(2) Job Find. Rate	(3) ln Cont. Claims	(4) AC	(5) GS Worker's Gap
Y= Δ Wage Growth	0.162***	0.146***	-0.089***	-0.023	0.161***
	(0.027)	(0.045)	(0.026)	(0.076)	(0.027)
Observations	134	134	134	111	134
R^2	0.173	0.117	0.126	0.003	0.203
Indep. Var	**(6) Hires Rate**	**(7) Hires/Vac.**	**(8) NFIB Difficulty Hiring**	**(9) CB Jobs Availability**	**(10) Separation Rate**
Y= ΔWage Growth	0.117	-0.264***	0.215***	0.171***	-0.034
	(0.081)	(0.049)	(0.041)	(0.034)	(0.042)
Observations	133	91	121	134	134
R^2	0.037	0.291	0.204	0.158	0.007

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

B.3 Industry Analysis

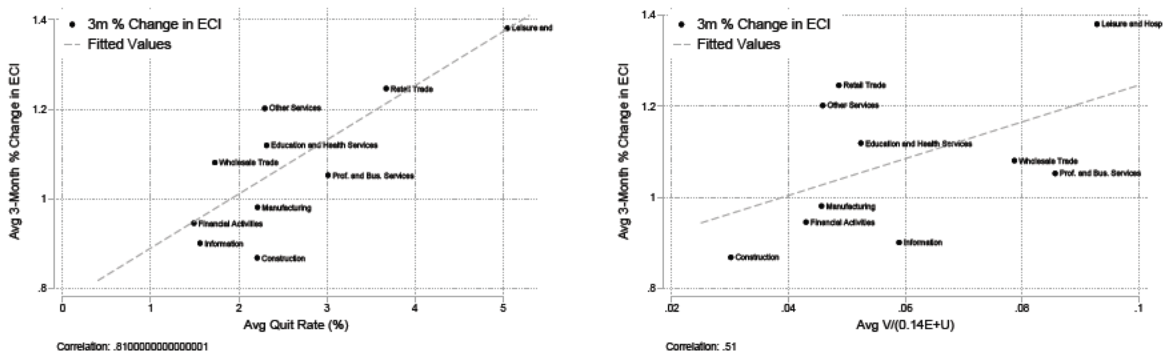
In this section we analyze wage growth in the cross-section of industries and how it correlates with quits and labor market tightness. We start by reporting variation across industries in recent data. We plot average 3-month ECI growth between 2020:q4 and 2024:q2 against the average quit rate over the same period for each industry and show the resulting scatterplot in Panel (a) of Figure A. 2. The figure shows that average wage growth and quits are strongly correlated in the cross-section of industries (correlation: 0.81). Panel (b) plots a similar diagram for $V/(0.14E + U)$ against average wage growth and shows a positive correlation of 0.51.[13]

Industries with more quits see significantly higher wage inflation. Industries with more va-

[13] We do not have the measure V/ES available at the industry-level since we lack measures of nonemployed that search and nonemployed that do not search by industry.

Figure A. 2: Average Wage Growth in the Cross-Section 2020:Q4-2024:Q2

(a) Quits (b) $V/(0.14 \cdot E + U)$



Notes: Left panel shows a scatterplot of the average quits rate between 2020:q4 and 2024:q2 against average 3-month ECI growth over the same time period across industries. Right panel shows a scatterplot with the average ratio of job openings over $0.14 \cdot \mathrm{E} + \mathrm{U}$ against the average 3-month ECI growth rate.

cancies also do, but the correlation is a bit weaker. For example, Leisure and Hospitality and Retail both boomed in the post-Covid era. These industries saw greater quits but also greater wage inflation.

In order to control for industry and time fixed effects, we now turn to regression specifications that will deliver the connection between quits, vacancies and nominal wage growth. By better understanding the variation at the industry level, we can both further test the mechanism of our model and understand the explanatory power in the cross-section as well as aggregate. We run similar regressions as equation (10) at the industry-level:

$$\Pi^w_{it} = \beta_1 X_{it} + \gamma_i + \rho_t + \epsilon_{it}, \tag{8}$$

where i indexes the industry, t indexes the quarter, Π^w_{it} is 3-month ECI wage growth, X_{it} is a labor market variable of interest, and γ_i and ρ_t are industry and time fixed effects, respectively. We construct industry-level unemployment, tightness, and quits measures from the CPS and from JOLTS. Since we do not have granular information on nonemployed workers by industry, we do not use V/ES but instead define searchers as $0.14E + U$, consistent with the calibration by Bloesch, Lee, and Weber (2024) where $\lambda_{EE} = 0.14$. Regression results for the period 2001:q1-2024:q2 are in Table A. 7 below.

The results indicate that industries with stronger wage growth tend to be those with a higher rate of quits and a greater tightness as measured by our tightness measure. As shown in columns 2 and 3, both of these variables have a significant effect on wage growth at the industry-level. A one standard deviation increase in the tightness measure $V/(0.14 \cdot E + U)$ (0.03) is associated with 0.16

Table A. 7: ECI Wage Growth and Labor Market Characteristics

	(1) Δ % Wage	(2) Δ % Wage	(3) Δ % Wage	(4) Δ % Wage	(5) Δ % Wage	(6) Δ % Wage
Unemployment	-0.036				-0.013	-0.021
	(0.029)				(0.024)	(0.023)
$V/(0.14E+U)$		0.157**				0.113***
		(0.049)				(0.039)
Quits Rate			0.226***		0.223**	0.171**
			(0.066)		(0.068)	(0.057)
V/U				0.010		
				(0.027)		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	926	926	926	926	926	926
Within R^2	0.001	0.016	0.019	0.000	0.019	0.026

Notes: Table shows results from a regression of 3-month wage changes from the ECI on labor market characteristics, with variation at the NAICS 2-digit level. Independent variables are standardized to have zero mean and standard deviation of one. Standard errors clustered at industry-level are in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

p.p. higher wage growth. A one standard deviation increase in the quits rate (0.93) translates into about 0.23 percentage point higher wage growth. In contrast, the industry-level unemployment rate and the V/U ratio no longer have a significant effect on industry-level wage growth. It is possible that the unemployment rate is not well-measured at the industry-level since workers can switch across industries.

C Wages and Productivity

The main message of this paper is the importance of labor market conditions for predicting nominal wage growth, with particular emphasis on vacancies over effective searchers or quits, rather than the unemployment rate. Section 3.3 pointed out that at the national level productivity does not have a discernable effect on wages. In this section, we provide some further empirical analysis of the relationship between productivity growth and nominal wage growth at the industry level.

C.1 Industry-Level Analysis

We now expand the analysis of Section 3.3 to the industry-level. We take labor productivity from the BLS at the NAICS 2-digit level, and run similar regressions as before at the industry level. The following equation is reported in Table A. 8,

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

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

Table A. 8: ECI and Productivity

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

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

Unlike the national regressions in the main text, wages show a stronger response to productivity in the industry-level regressions. As can be seen in Column 3, with industry and year controls, a 1% increase in productivity in a year is associated with a 0.15% increase in wages in the industry, significant at the 10% level. This may reflect the fact that unlike in national regressions, which look at the effect of shocks on all firms, industries will which receive positive shocks may be able to outcompete other industries for workers by raising wages.

D Additional V/U Discussion

We re-run our analyses using the alternative tightness measure V/U as is used in Benigno and Eggertsson (2023, 2024). As in the main text, we first run regressions of the form

$$\Pi_t^w = \beta_0 + \beta_1 X_t + \epsilon_t, \tag{10}$$

where Π_t^w is wage inflation measured by the 3-month change in the ECI between quarter $t-1$ and quarter t and X_t is the labor market variable of interest in quarter t. As in the main text, we run the regression for the period 1990:q2-2024:q2, as dictated by the availability of quits. Table A. 9 shows the results from running this regression using V/U and quits separately and jointly.

Table A. 9: Wage Growth Regressions (contemporaneous) with V/U and Quits

	(1) Δ % Wage	(2) Δ % Wage	(3) Δ % Wage
V/U	0.172***		0.043*
	(0.0172)		(0.0243)
Quits Rate		0.200***	0.167***
		(0.0141)	(0.0229)
Observations	137	137	137
R^2	0.406	0.551	0.561

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

The first column shows that V/U has a strong positive effect on wage growth. A one standard deviation increase in this tightness measure (0.389) is associated with an increase in 3-month ECI wage growth of 0.17 p. p. Column 2 replicates our results with the quits rate from the main text. Column 3 shows both variables together. When combined with the quits rate in the same regression, the magnitude and significance of the coefficient on V/U deteriorates sharply. This effect stands in sharp contrast to our findings in the main text, where the coefficient on V/ES remained significant at the 1 percent level when included in the regression with quits.

Table A. 10 shows the results when we run regression (10) with one-quarter ahead wage growth (between t and $t+1$) analogous to Table A.3 in the main text. As before, we find that V/U alone has a significant effect on wage growth. However, column 3 shows that once we include V/U together with quits, the coefficient on V/U becomes insignificant. Thus, V/U does not seem to hold any further explanatory power for wages once we control for quits, in contrast to V/ES.

Table A. 11 presents similar regressions using 12-month changes in ECI, where the dependent variable is wage growth between quarter t and quarter $t+4$. The results are consistent with our findings at the 3-month level. Again, the coefficient on V/U becomes insignificant, and in fact negative, once it is used jointly with the quits rate to predict wage growth.

Table A. 10: Wage Growth Regressions (3-month ahead) with V/U and Quits

	(1)	(2)	(3)
	Δ % Wage	Δ % Wage	Δ % Wage
V/U	0.165***		0.013
	(0.0180)		(0.0240)
Quits Rate		0.205***	0.195***
		(0.0140)	(0.0243)
Observations	136	136	136
R^2	0.378	0.588	0.589

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

Table A. 11: Wage Growth Regressions (12-month ahead) with V/U and Quits

	(1)	(2)	(3)
	Δ % Wage	Δ % Wage	Δ % Wage
V/U	0.619***		-0.062
	(0.103)		(0.111)
Quits Rate		0.765***	0.813***
		(0.0580)	(0.105)
Observations	133	133	133
R^2	0.450	0.758	0.760

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

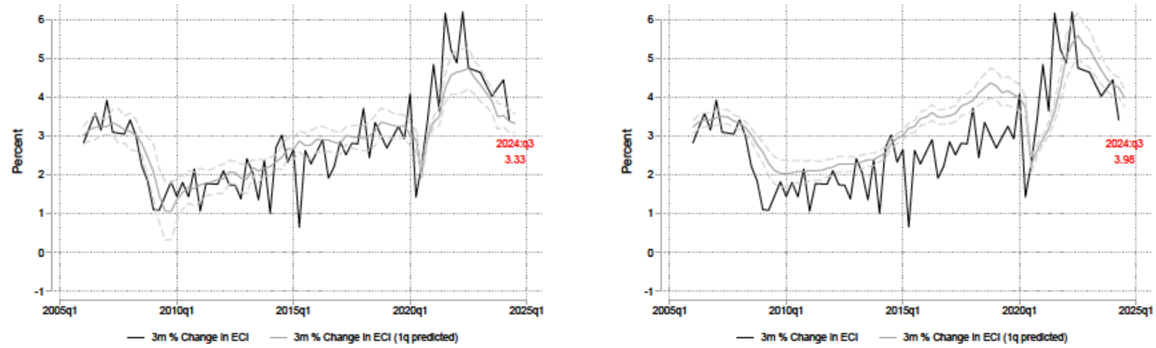
Figure A. 3 performs the out-of-sample prediction of the one-quarter ahead 3-month annualized wage growth from Section 4.1 of the paper. The left panel replicates Figure 4 of the paper. It compares the actual wage growth (black) to the predicted wage growth (gray) using our preferred measures quits and V/ES as predictors. The gray dashed line shows 90 percent confidence intervals. The right panel shows the same plot when we use V/U to predict wage growth. Overall, this alternative prediction does reasonably well, though worse than the baseline. The root mean squared error (RMSE) of the forecast, computed as the square root of the summed squared deviation of the black line from the gray line, rises from 0.64 in the baseline to 0.93 with V/U, a 46 percent increase. The main reason for the larger RMSE for the forecasts using the V/U ratio is that the predicted values of wage growth between 2015-2020 are systematically higher than the realized wage growth.

Figure A. 4 zooms in on the most recent period, since 2020:q1. The figure compares the actual wage growth (black) against the one-quarter ahead prediction from using our baseline variables V/ES and the quits rate (gray) and the prediction using V/U (blue). For this period, the two predictions are relatively similar. Nevertheless, the RMSE is still higher for the prediction with the V/U ratio compared to our baseline: 1.09 compared to 0.88. Thus, even for the recent period, our baseline approach performs better than V/U.

Figure A. 3: One-Quarter Forecast of 3-Month ECI Growth

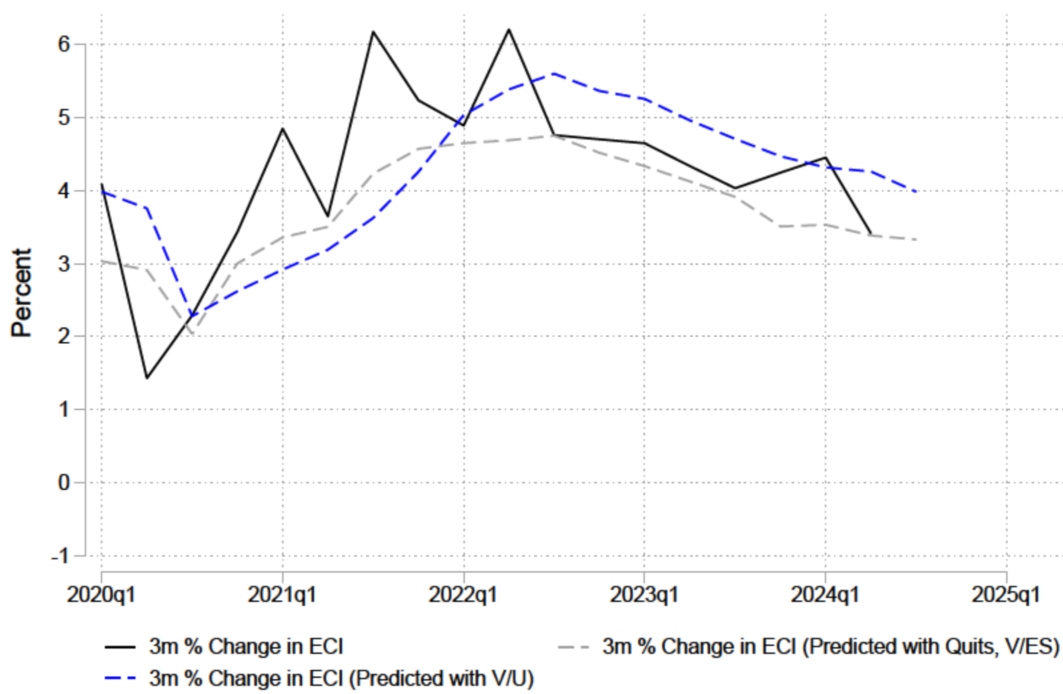
(a) Using V/ES and Quits for the Forecast

(b) Using V/U for the Forecast



Notes: Figure shows annualized 3-month ECI wage growth (black) against the predicted annualized 3-month wage growth from one quarter earlier (gray). 90 percent confidence bands are included.

Figure A. 4: One-Quarter Forecast of 3-Month ECI Growth Since 2020



Notes: Figure shows annualized 3-month ECI wage growth (black) against the predicted annualized 3-month wage growth from one quarter earlier (gray). 90 percent confidence bands are included.