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ABSTRACT

Since the outset of the Covid-19 pandemic, labor market indicators that traditionally move together have been sending different signals about the degree of slack in the U.S. labor market. While some indicators on the supply-side, such as the prime-age employment-to-population ratio, suggest that there is still some slack in the labor market, other indicators on the demand-side, such as the job vacancy rate and the quits rate, imply that the labor market is already very tight. In light of these divergent signals, this paper compares alternative labor market indicators as predictors of wage inflation. Using national time series and state cross-section data, we find (i) unemployment is a better predictor of wage inflation than non-employment and (ii) vacancy rates and quit rates have substantial predictive power for wage inflation. We highlight the fact that vacancy and quit rates currently experienced in the United States correspond to a degree of labor market tightness previously associated with sub-2 percent unemployment rates. Finally, we show that predicted firm-side unemployment has dominant explanatory power with respect to subsequent inflation. Our results, along with a cursory analysis of labor force participation information, suggest that labor market tightness is likely to contribute significantly to inflationary pressure in the United States for some time to come.

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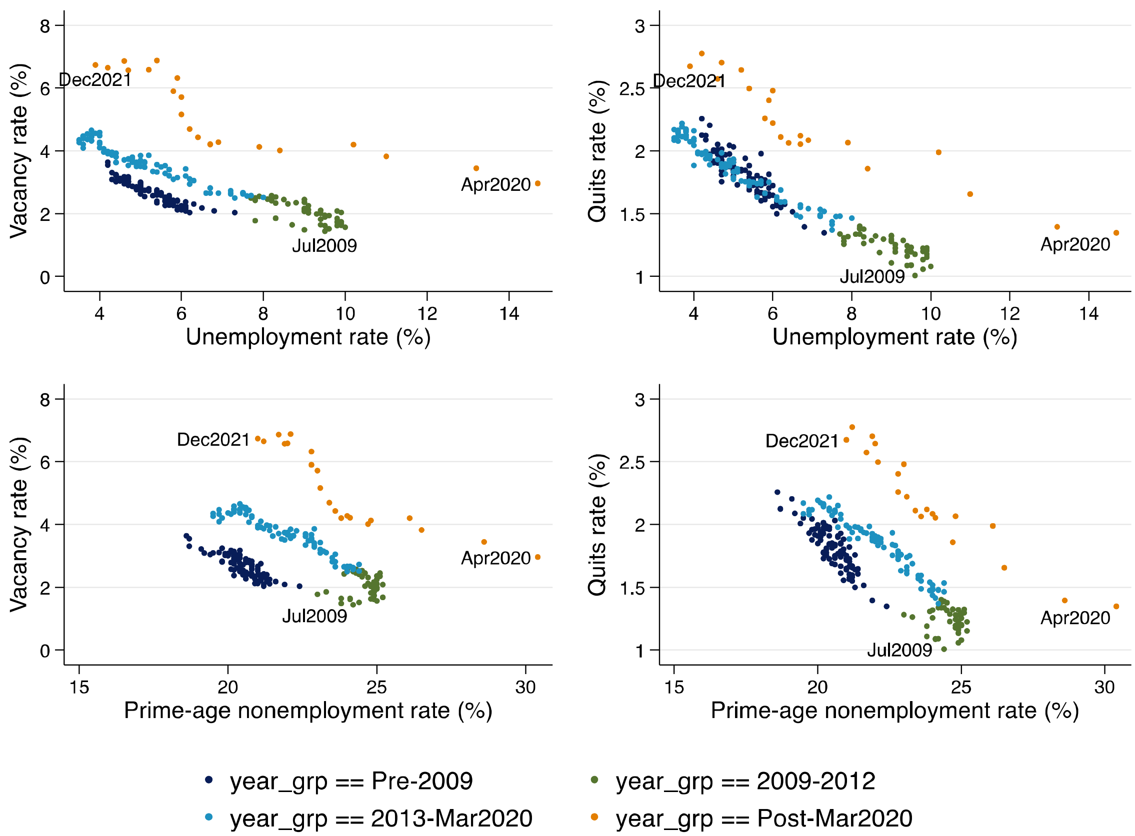
1 Introduction

Economists have typically turned to common slack measures, such as the unemployment rate or the job vacancy rate, to assess labor market tightness and predict nominal wage growth. Historically, measures of slack on the supply-side, like the unemployment rate and the prime-age (25-54) nonemployment rate[1], have moved in tandem with measures of slack on the demand-side, such as the job vacancy rate and the quits rate, meaning that different indicators gave broadly corroborative signals of labor market tightness. Since the beginning of the Covid-19 pandemic, however, the supply-side indicators and the demand-side indicators have diverged significantly. While the unemployment rate and prime-age nonemployment rate remain elevated at late-2017 levels and imply modest degrees of slack, the job vacancy rate and quits rate have surged to series highs[2] and imply a very tight labor market. We illustrate these trends with Beveridge type curves in Figure 1, showing how the relation between firm-side and household-side measures have shifted outwards since the beginning of the pandemic[3].

[1] This is equivalent to one minus the prime-age employment-to-population ratio.
[2] As of December 2021, the BLS Job Openings and Labor Turnover Survey (JOLTS) reported a seasonally adjusted job vacancy rate of 6.8% (a near-record high, and much higher than any vacancy rate before 2021) and a seasonally adjusted quits rate of 2.9% (the second highest quits rate on record).
[3] Data from the BLS Job Openings and Labor Turnover Survey is only available from January 2001 to November 2021. The unemployment rate is the U-3 unemployment rate. Prime-age nonemployment is the share of the civilian noninstitutional population aged 25-54 that is not working. The vacancy rate is the level of job vacancies divided by the size of the civilian labor force, and the quits rate is the level of quits divided by the size of the civilian labor force. All values are seasonally adjusted.

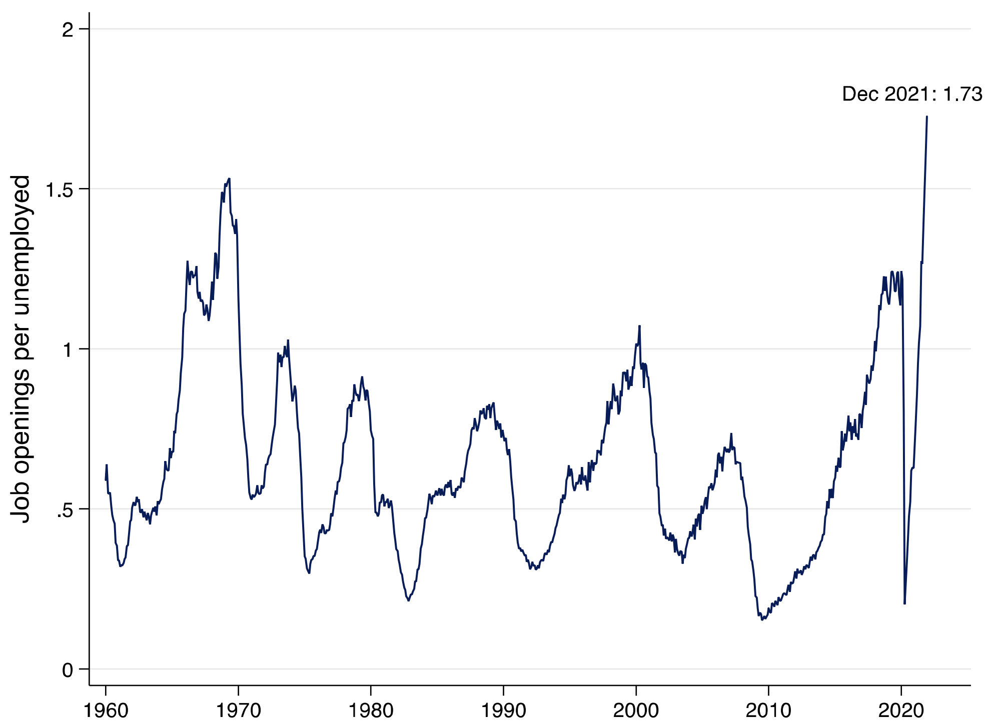
Figure 1: Firm-side vs household-side slack measures, Jan 2001 – Dec 2021



Source: Bureau of Labor Statistics Current Population Survey (CPS) and Job Openings and Labor Turnover Survey (JOLTS) via FRED; authors' calculations.

Given the divergent signals coming from the labor market, how are we to assess the current degree of slack in the labor market? The original Phillips curve suggested that when the unemployment rate is lower, wage inflation is higher. But estimates for the non-accelerating inflation rate of unemployment (NAIRU) are highly uncertain, and the unemployment rate does not adequately capture all movements in the labor market that are significant for wage inflation. As an alternative to the unemployment rate, Federal Reserve Chairman Jerome Powell has suggested looking at employment indicators, like the prime-age employment-to-population ratio, to assess labor market slack[4]. The prime-age employment ratio accounts for both the unemployment rate and labor force participation, and thus may be more reflective of full employment. Beyond the unemployment rate and employment ratio, measures such as the quits rate, the job vacancy rate, and the number of job openings per unemployed are also relevant for assessing labor market tightness, as they provide important information on labor market conditions facing employers. Figure 2 plots the monthly ratio of job openings to the number of unemployed dating back to 1960, showing how the number of job openings per job seeker reached a record level of 1.73 in December 2021.

Figure 2: Historical Vacancy to Unemployment Ratio, Jan 1960 – Dec 2021



Notes: Vacancy data before 2001 uses vacancy estimates constructed from Barnichon (2010) using the Help-Wanted Index published by the Conference Board. All values are seasonally adjusted.
Source: Bureau of Labor Statistics Current Population Survey (CPS) and Job Openings and Labor Turnover Survey (JOLTS) via FRED, Barnichon (2010); authors' calculations

[4] Board of Governors of the Federal Reserve System. "Speech by Chair Powell on Getting Back to a Strong Labor Market." February 10, 2021. https://www.federalreserve.gov/newsevents/speech/powell20210210a.htm

In this paper, we take a general approach to evaluating labor market tightness by exploring the relationship between four different slack indicators – the U-3 unemployment rate, the prime-age employment ratio[5], the vacancy rate, and the quits rate – and measures of wage inflation. Our benchmark assessment at the aggregate level suggests that the U-3 unemployment rate is better than the prime-age employment ratio in predicting wage inflation, and that the job vacancy rate and the quits rate are comparable to the U-3 unemployment rate in their explanatory power. Motivated by the relative importance of the firm-side indicators, we proceed to estimate a firm-side equivalent unemployment rate by examining what unemployment rate is consistent with the current measures of the job vacancy rate and the quits rate. In December 2021, the predicted firm-side unemployment rate was between 1.2 to 1.7 percent, compared to the actual unemployment rate of 3.9 percent. We then evaluate the relative efficacy of these two unemployment rates in predicting past wage inflation using pre-pandemic data, and find that essentially all the predictive power is in our firm-side predicted unemployment rate. These results indicate that the firm-side equivalent unemployment rate is likely the best predictor of wage inflation, and suggests that we should currently be thinking about the labor market as very tight.

Given the limited information available in a single aggregate time series, we make use of time series cross-section data at the state level as a further robustness check. The state-level results fully corroborate our findings at the aggregate level, and show that states' vacancy and quit rates are comparable to the local unemployment rate in their explanatory power in predicting wage inflation. We also find that the estimated firm-side unemployment rates at the state-level are highly

[5] We use the employment-to-population ratio for prime-age adults between the ages of 25-54 to avoid capturing effects of demographic changes, such as an ageing population.

predictive of subsequent wage inflation. These results strongly confirm our conclusion that the job vacancy rate and quits rate are together highly significant for predicting wage inflation.

Finally, we assess the implications of our analysis for the current inflationary outlook by disaggregating the factors that have contributed to the labor supply shortfall and the outward shift in the Beveridge type curves. We estimate that labor force participation is likely to remain significantly depressed through at least the end of 2022, with excess retirements, Covid-19 health concerns, immigration restrictions, changes in workers' tastes proxied by reservation wages, and shifts in the demographic structure explaining most of the labor shortfall. This suggests that the labor market is likely to continue to be very tight moving forward unless there is a considerable slowdown in labor demand.

Related Literature

Inflation forecasts based on labor market tightness typically use estimates of the unemployment gap to proxy for labor market slack. Recent research, however, suggests that the unemployment gap may be an insufficient indicator of labor demand conditions, and ought to be augmented with other signals from the labor market.

There are various reasons why the unemployment gap is inadequate to fully capture labor market tightness, particularly in the context of the Covid-19 pandemic. First, it is generally hard to measure, given the high degree of uncertainty around the NAIRU estimate. Record levels of structural change during the Covid-19 pandemic, for example, is likely to raise the NAIRU estimate. Second, the composition of unemployed workers, particularly the distribution of long-term unemployed versus short-term unemployed, also affects the degree of tightness in the labor market. Krueger, Cramer, and Cho (2014) argue that the unemployment rate can overestimate the degree of labor market slack, since the long-term unemployed exert significantly less wage pressure than other unemployed individuals. Third, the unemployment rate does not capture hidden unemployment (people who are not actively searching for a job, but who would rejoin the workforce if the job market were stronger) or employed individuals who are looking for work – both of which are significant for wage dynamics.

Given these shortcomings in the unemployment gap, many studies have formulated alternative indicators to better proxy for labor market slack. One approach in the literature, dating back to at least Perry et al (1970), is to take into account additional margins of labor market underutilization not captured by the U-3 unemployment rate. For example, Blanchflower and Levin (2015) calculate the degree of hidden unemployment in the U.S. economy and find that it exerts significant downward pressure on wages; Faberman et al. (2020) create an aggregate gap in desired hours worked, and find that it accounts well for wage movements; Krueger, Cramer, and Cho (2014) focus on the long-term unemployed and find that they exert significantly less pressure on wages. A second approach found in the literature is motivated by the canonical Mortenson, and Pissarides (1994) search and matching model of the labor market, and ties the unemployment rate to job openings to assess labor market tightness. For example, Abraham et al. (2020) construct a measure of labor market tightness based on the ratio of vacancies to effective searchers, and Faccini and Melosi (2021) use the on-the-job search rate to account for recent missing inflation.

Our paper broadly relates to these past efforts to measure labor market slack by comparing the predictive power of four different slack indicators – the U-3 unemployment rate, the prime-age employment ratio, the vacancy rate, and the quits rate – on wage inflation. Our choice to include the vacancy rate and quits rate is motivated by a growing interest among economists to look at firm-side indicators to assess labor market tightness. A high vacancy rate signals a high demand for labor and puts upward pressure on wages as firms compete to attract workers. A high quits rate signals that workers are confident enough to leave their jobs to search for a better opportunity, and can put upward pressure on wages since job switchers drive up wages as they move up the job ladder. These firm-side indicators are particularly relevant today given the record number of vacancies and quits in recent months.

Our work closely relates to recent analysis by Furman and Powell (2021), who investigate the best univariate predictor of changes in wage and price growth in the United States since the early 2000s, and find that the quits rate is the best predictor of nominal wage growth, followed by prime-age nonemployment and total unemployment[6]. Our paper has several important differences. While they use publicly available aggregate data from 2001 to present, we extend our vacancy and quits series back to 1990 to make use of a longer time-series, and we supplement our analysis with data available at the state level. Our empirical approach also emphasizes the estimation of a firm-side unemployment rate, which has the advantage of tying together the supply-side and firm-side measures into a single indicator. We find that this firm-side equivalent unemployment rate accounts well for historical movements in nominal wages.

The paper is organized as follows. Section 2 describes the data used and our empirical approach. In Section 3, we present the empirical results from our wage Phillips curve regressions at the aggregate and local-level, construct a synthetic firm-side unemployment rate that is consistent with the current vacancy rate and quits rate, and compare the efficacy of this firm-side unemployment rate with the actual unemployment rate in predicting wage inflation. Section 4 investigates the current employment shortfall and provides analysis on the likely trajectory of labor

[6] Furman and Powell (2021). What is the best measure of labor market tightness? *Peterson Institute for International Economics*. Nov 22, 2021. https://www.piie.com/blogs/realtime-economic-issues-watch/what-best-measure-labor-market-tightness#_ftnref1

force participation over the coming year. Section 5 concludes and discusses the implications for inflation moving forward.

2 Data and Empirical Strategy

2.1 Aggregate and State-Level Data

Wage data for our aggregate Phillips curve models comes from three publicly available wage datasets. Our primary specification uses the Economic Policy Institute's microdata extracts of the Current Population Survey Outgoing Rotation Group (CPS-ORG)[7]. We also use data from the BLS Current Employment Statistics production/nonsupervisory average hourly earnings series, which has monthly earnings data available from 1965 to present, and the Employment Cost Index (ECI), which is adjusted for worker composition and has quarterly data on the wages and salaries of all private industry workers from 2002 to present.

Our aggregate job vacancy data uses the BLS JOLTS (Job Openings and Labor Turnover Survey) series on monthly job vacancies from December 2000 to September 2021. For some of our regressions, we extend the JOLTS vacancy series with data constructed by Barnichon (2010), who makes use of the Help-Wanted Index published by the Conference Board to create a historical vacancy rate series from 1960 to 2001. The job vacancy rate throughout this paper is defined as the number of monthly job openings divided by the size of the labor force, to be consistent with Barnichon (2010). Our monthly quits data also comes from the BLS JOLTS. For our models that use quarterly data, we use quarterly job quits estimates from Davis, Faberman, and Haltiwanger (2012), who construct a quarterly dataset of worker quits dating back to 1990[8]. The DFH-JOLTS

[7] This dataset has monthly wage data available from 1979 to present, and is restricted to those ages 16 and above with a positive earner sample weight and in the outgoing rotation months. We use repeated cross-section data to calculate average and median wages.
[8] The DFH-JOLTS quits series has recently been extended to 2021.

quits series is constructed by combining cross-sectional worker flow relations with data on the cross-sectional distribution of establishment growth rates from BED data, and has the advantage over the JOLTS quits series by extending quits data back an extra 11 years. We make use of both the DFH-JOLTS estimates and regular JOLTS series throughout this paper.

The analysis at the state-level uses publicly available data from local labor markets (50 states, not including District of Columbia). For unemployment rates and labor force participation rates, we use seasonally adjusted BLS series, and for vacancy rates and quits rates, we use JOLTS state-level data from Dec 2000 to Aug 2021[9]. Our wage data at the state-level comes from 2 sources: i) EPI microdata extracts of CPS-ORG data, and ii) hourly wage data across all occupations from the BLS Occupational Employment and Wage Statistics (OEWS) database. We use CPI-U data by census region to construct our weighted lagged inflation variable to control for expected inflation.

2.2 Empirical Approach

For our baseline regressions at the aggregate level, we run wage Phillips curve regressions including different combinations of our explanatory variables. At the simplest level, these regressions take the following form:

$$log\, wage_t - log\, wage_{t-1} = \alpha + \beta slack_t + \gamma lagged\ inflation_t + \varepsilon_t \qquad (1)$$

where $slack_t$ is a vector of slack variables, and lagged inflation is a 3-year weighted average of CPI that assigns a weight of three to inflation in period *t*-1, a weight of two to inflation in period *t*-2, and a weight of one to inflation in period *t*-3, to control for expected inflation.

[9] At the state-level, there are no estimates for vacancies and quits prior to Dec 2000, so all of our state-level models begin in 2001.

For our aggregate wage Phillips curve regressions, we begin by calculating the quarterly mean of monthly year-over-year percent changes in the average hourly wage, and quarterly means for the monthly levels of our slack variables. We then regress the 4-quarter moving average of quarterly year-over-year wage growth on the 4-quarter moving average of our slack indicators. It is not immediately clear to us how long of a lag exists between changes in our slack measures and changes in wages, so we also run the same specification with 4-quarter lags and 8-quarter lags, and report the cumulative dynamic multiplier of the lagged effect and the contemporaneous effect. The specification for our distributed-lag model with 4-quarter lags is as follows, where each observation is a quarterly mean:

$$\frac{1}{4}\sum_0^3 \Delta\, log\ wage_{\ t-i} = \alpha + \beta \frac{1}{4}\sum_0^3 slack_{t-i} + \sum_{j=1}^{j=4} \rho_j \frac{1}{4}\sum_{i=0}^{i=3} slack_{t-i-j} +$$

$$\gamma \frac{1}{6}\left[3 * \frac{1}{4}\sum_4^7 inflation_{t-i} + 2 * \frac{1}{4}\sum_8^{11} inflation_{t-i} + \frac{1}{4}\sum_{12}^{15} inflation_{t-i}\right] + \varepsilon_t \qquad (2)$$

We estimate these models using data from 1990, the first year all four measures of slack are available, through 2019 to avoid changes in the relationships caused by the Covid-19 pandemic[10]. For our state-level regressions, we estimate the model using data from 2001 to 2019, given the lack of available vacancy and quits data at the local level before 2001.

After estimating the wage Phillips curve models, we then use monthly data to predict an equivalent firm-side unemployment rate given the observed values of the vacancy rate and the quits rate. Our model specification to predict the firm-side unemployment rate is as follows:

[10] To account for autocorrelation in our observations, we use Newey-West heteroskedasticity and autocorrelation robust standard errors. We specify a lag length using the Stock and Watson (2007) "rule of thumb" lags=0.75*T^(1/3).

$$Predicted\ unemployment\ rate_t = \alpha + \beta \sum_0^{12} log\ vacancy\ rate_{t-i} + \delta \sum_0^{12} \log quits\ rate_{t-i} + \gamma * time\ trend_t + \theta * structural\ break_t + \varepsilon_t \quad (3)$$

We estimate this model using data from January 2001 to December 2019 to avoid any changes induced by the Covid-19 pandemic[11]. The choice to use a linear-log model was informed by the parabolic nature of the relationship between the unemployment rate and the vacancy and quits rates, and the overall fit of the model determined by the adjusted R-squared (a linear model would predict a significantly lower firm-side unemployment rate)[12]. Our selection for the structural break is July 2009, which follows Michaillat and Saez (2019), who found a break in the relationship between the job vacancy rate and the unemployment rate at this time. Our choice of 12-month lags corresponds to the lag length suggested by the Akaike Information Criteria (AIC). We also repeat the same specification using 4-month lags, which is the lag length suggested by the Bayesian Information Criteria (BIC). Using the estimated results, we predict out-of-sample values for the unemployment rate given the observed vacancy and quits rate from January 2020 to present.

We next extend our analysis to time-series cross-section data at the state level. Using state-level data, we repeat the regressions specified above, except we aggregate our data to the state-year level, since monthly and quarterly wage data can be noisy for local labor markets. For our state level wage Phillips curve regressions, we check for robustness using model specifications that include 3-year moving averages and one- and two-year lags. Finally, using equation (3), we

[11] We choose January 2001 as a start date since monthly job vacancy and quits data is only available beginning in 2001.

[12] We also tried a quadratic model, but the negative sign on the squared term for vacancies and quits implied that high out-of-sample values of vacancies and quits were associated with increases in the unemployment rate – which is counterintuitive. We thus decided to use a log model, and report results for many different model specifications.

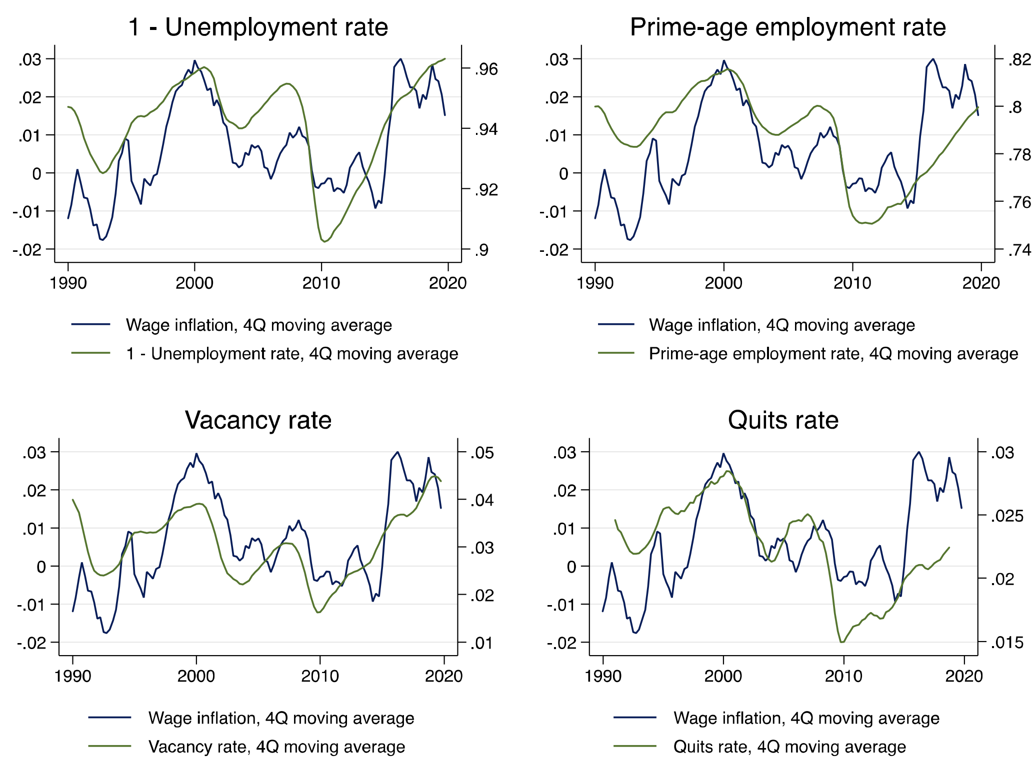
predict 50 state-level firm-side unemployment rates, and estimate wage Phillips curve models with firm-side and actual unemployment rates, using state and year fixed effects.

3 Empirical Results

3.1 Which slack indicator best predicts wage inflation at the aggregate level?

We begin by investigating which of our four slack indicators is most significant for predicting wage inflation. Figure 3 shows timeseries plots of mean wage growth, calculated from CPS-ORG microdata and conditioned on lagged inflation, versus the 4-quarter moving average of each slack indicator, using historical data from 1990 to 2019. The figure shows strong relationships with clear lags between the level of each slack measure and wage inflation.

Figure 3: Wage inflation vs different slack indicators, 1990-2019



Notes: The left axis corresponds to the 4-quarter moving average of wage inflation and the right axis corresponds to the level of each slack indicator. We plot one minus the unemployment rate to be directionally consistent with the other indicators. Vacancy date comes from Barnichon (2010) and quits data comes from the extended Davis, Faberman & Haltiwanger (2012) series.
Source: Bureau of Labor Statistics, Barnichon (2010), Davis, Faberman & Haltiwanger (2012); authors' calculations

Table 1 presents our regression results comparing the relative importance of our two supply-side indicators – the unemployment rate and prime-age employment ratio – in predicting historical wage inflation. The prime-age employment ratio is decomposed into its two components, the unemployment rate and the labor force participation rate, to compare which is more significant[13]. The dependent variables are 4-quarter moving averages of the year-over-year percent change in wages, where wages are CPS-ORG mean wages in columns 1-3, CPS-ORG median wages in columns 4-6, and as the BLS production/nonsupervisory average hourly earnings in column 7-9. For each wage series, we report the results for the contemporaneous regression, as well as the cumulative multiplier for regressions including 4-quarter lags and 8-quarter lags. We estimate this model using data from 1990 to 2019 to be consistent with the rest of the models in this section (quarterly data for the quits rate is only available beginning in 1990)[14].

Table 1: Wage inflation on decomposed prime-age employment-to-population ratio, 1990 – 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables are 4-quarter moving average of year-over-year % change in wages	CPS-ORG Average Contemp	CPS-ORG Average 4-quarter lags	CPS-ORG Average 8-quarter lags	CPS-ORG Median Contemp	CPS-ORG Median 4-quarter lags	CPS-ORG Median 8-quarter lags	Prod/Nonsupervisory Average Contemp	Prod/Nonsupervisory Average 4-quarter lags	Prod/Nonsupervisory Average 8-quarter lags
Prime-age unemployment rate (25-54)	-0.47*** (0.059)	-0.57*** (0.10)	-0.47*** (0.16)	-0.41*** (0.070)	-0.51*** (0.13)	-0.62*** (0.23)	-0.18** (0.071)	-0.26*** (0.078)	-0.20** (0.087)
Prime-age labor force participation rate (25-54)	0.20 (0.18)	0.098 (0.18)	0.14 (0.22)	0.36* (0.20)	0.26 (0.25)	0.076 (0.33)	0.39*** (0.074)	0.30*** (0.088)	0.31*** (0.095)
Weighted lagged inflation	0.13 (0.13)	0.063 (0.15)	-0.011 (0.13)	0.063 (0.21)	0.11 (0.21)	0.097 (0.23)	0.094 (0.096)	0.034 (0.088)	-0.011 (0.092)
Constant	0.087*** (0.026)	0.077** (0.030)	0.075** (0.029)	0.11*** (0.037)	0.083* (0.049)	0.067 (0.056)	0.094*** (0.013)	0.085*** (0.014)	0.083*** (0.014)
Observations	120	120	120	120	120	120	120	120	120
R-squared	0.60	0.68	0.73	0.41	0.48	0.53	0.64	0.75	0.80

Notes: All the coefficients for the lagged regressions are the cumulative dynamic effect of the level plus all the lags. Weighted lagged inflation uses a 3-year weighted average of CPI data. Newey-West standard errors (HAC) in parentheses using a lag order of 5, *** p<0.01, ** p<0.05, * p<0.1

[13] The prime-age employment-to-population ratio is mathematically equivalent to the labor force participation rate * (1- unemployment rate)

[14] Results look similar if we extend the time series back to 1979, when the CPS-ORG microdata is first available.

Using the CPS-ORG composition-adjusted mean and median wages, the unemployment rate is much more significant than the labor force participation rate in explaining wage inflation. Using the BLS production/nonsupervisory average hourly earnings series (which is not composition-adjusted), both the labor force participation rate and the unemployment rate are highly significant in predicting wage inflation.

Next, we compare the relative efficacy of the headline unemployment rate (U-3) with our two demand-side indicators, the vacancy rate and the quits rate. Table 2 presents the results from wage Phillips curve models with different combinations of the unemployment rate, the vacancy rate, and the quits rate. The dependent variable is the 4-quarter moving average of year-over-year percent changes in mean CPS-ORG wages. Columns 1-3 regress nominal wage growth on the 4-quarter moving average of the unemployment rate and the vacancy rate, Columns 4-6 regress nominal wage growth on the unemployment rate and the DFH-JOLTS quarterly quits estimates, and Columns 7-9 use the unemployment rate, the vacancy rate, and the DFH-JOLTS quits rate.

Table 2: Wage inflation on the unemployment rate, vacancy rate, and quits rate, 1990-2019

Dependent variables are 4-quarter MA of YoY % change in mean CPS-ORG wages	(1) Contemp	(2) 4-quarter lags	(3) 8-quarter lags	(4) Contemp	(5) 4-quarter lags	(6) 8-quarter lags	(7) Contemp	(8) 4-quarter lags	(9) 8-quarter lags
Unemployment rate, 4-quarter moving average	-0.43*** (0.10)	-0.35*** (0.088)	-0.36*** (0.11)	-0.38*** (0.12)	-0.28* (0.15)	-0.29 (0.20)	-0.32** (0.16)	-0.13 (0.17)	-0.14 (0.22)
Vacancy rate, 4-quarter moving average	0.14 (0.25)	0.48** (0.21)	0.56** (0.23)				0.23 (0.28)	0.70*** (0.22)	0.80*** (0.20)
Quits rate, 4-quarter moving average				0.19 (0.24)	0.41* (0.23)	0.41* (0.23)	0.15 (0.23)	0.33 (0.24)	0.34 (0.31)
Weighted lagged inflation	0.33*** (0.093)	0.19* (0.11)	0.16 (0.14)	0.26* (0.13)	-0.075 (0.14)	-0.18 (0.19)	0.31** (0.12)	0.079 (0.11)	0.040 (0.20)
Observations	112	108	103	112	108	103	112	108	103
R-squared	0.58	0.70	0.71	0.58	0.69	0.71	0.59	0.73	0.76

Notes: All the coefficients for the lagged regressions are the cumulative dynamic effect of the level plus all the lags. The vacancy rate data comes from the Barnichon (2010) estimates in order to extend the series back to 1990. Weighted lagged inflation uses a 3-year weighted average of CPI data. Newey-West standard errors (HAC) in parentheses using a lag order of 5. *** p<0.01, ** p<0.05, * p<0.1

The results show that the vacancy rate and the quits rate are broadly comparable to the unemployment rate in their ability to predict wage inflation. In particular, with 4-quarter and 8-quarter lags, both the vacancy rate and the quits rate come in more significant than the unemployment rate in predicting future nominal wage growth. In the model specification using all three slack variables and lags, the vacancy rate drives future wage inflation and is significant at the 1% level[15].

Table 3 provides additional robustness checks across different wage measures and different time periods. All regression specifications in Table 3 use the 4-quarter lags of the slack measures. Columns 1-4 use only the unemployment rate and the vacancy rate as explanatory variables, and show that the vacancy rate is highly significant over longer time periods, but has become less significant in explaining wage inflation compared to the unemployment rate since 2002[16]. Columns 5-8 use only the unemployment rate and the DFH-JOLTS quits series as explanatory variables, and show that the quits rate remains very significant across different time periods and wage series. Columns 9-12 include all three slack variables in the model, and provide further evidence that the vacancy rate and the quits rate are more significant than the unemployment rate in explaining nominal wage growth.

[15] These results hold when using the JOLTS quits series instead of the DFH-JOLTS series, and for different regression specifications that use annualized averages, rather than quarterly means.

[16] This is likely due to the shift outward in the Beveridge curve after 2009, where job vacancies jumped immediately during the recovery while the unemployment rate and nominal wage growth lagged behind.

Table 3: Different regression specifications for nominal wage growth on lagged slack indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables are 4-quarter lags of YoY % change in wages	CPS-ORG mean wages	CPS-ORG median wages	CPS-ORG mean wages	ECI	Prod/non supervisory wages	CPS-ORG median wages	CPS-ORG mean wages	ECI	Prod/nonsupervisory wages	CPS-ORG median wages	CPS-ORG mean wages	ECI
	1979-2019	1979-2019	2002-2019	2002-2019	1990-2019	1990-2019	2002-2019	2002-2019	1990-2019	1990-2019	2002-2019	2002-2019
Unemployment rate	-0.22***	-0.29**	-0.31**	-0.32***	-0.067	-0.30	-0.33***	-0.13**	-0.041	-0.25	-0.0046	-0.15
	(0.068)	(0.12)	(0.12)	(0.047)	(0.10)	(0.23)	(0.12)	(0.059)	(0.12)	(0.32)	(0.18)	(0.10)
Vacancy rate	0.73***	0.81***	0.45	-0.14					0.17	0.046	0.89***	-0.032
	(0.19)	(0.29)	(0.27)	(0.13)					(0.22)	(0.53)	(0.26)	(0.15)
Quits rate					0.43***	0.50	0.27	0.32***	0.42***	0.56	0.46	0.31**
					(0.14)	(0.40)	(0.24)	(0.11)	(0.15)	(0.43)	(0.29)	(0.14)
Weighted lagged inflation	0.56***	0.61***	0.16	0.18**	0.00022	-0.11	-0.097	0.094	0.076	-0.15	0.11	0.093
	(0.049)	(0.075)	(0.21)	(0.075)	(0.13)	(0.25)	(0.22)	(0.084)	(0.13)	(0.30)	(0.22)	(0.088)
Constant	0.0089	0.0053	0.032*	0.044***	0.0047	0.013	0.034*	0.0096	-0.0038	0.0068	-0.028	0.012
	(0.0081)	(0.014)	(0.018)	(0.0068)	(0.013)	(0.036)	(0.019)	(0.089)	(0.018)	(0.053)	(0.030)	(0.018)
Observations	157	157	65	65	108	108	65	65	108	108	65	65
R-squared	0.81	0.69	0.83	0.89	0.73	0.44	0.78	0.92	0.77	0.45	0.87	0.92

Notes: All the coefficients for the lagged regressions are the cumulative dynamic effect of the level plus all the lags. The vacancy rate data comes from the Barnichon (2010) estimates in order to extend the series back to 1965. Weighted lagged inflation uses a 3-year weighted average of CPI data. Newey-West standard errors (HAC) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Taken together, Tables 1-3 suggest that the unemployment rate is more important than the prime-age employment ratio in predicting wage inflation, and that the vacancy rate and the quits rate are at least as important as the unemployment rate in predicting wage inflation. Moreover, we find some evidence that the firm-side indicators become more significant at explaining wage inflation with one- or two-year lags.

3.2 Estimating a firm-side equivalent unemployment rate

What do these results imply for judging the inflationary outlook today? To answer this question, we proceed in two steps. We first estimate a firm-side equivalent unemployment rate by examining what unemployment rate is consistent with the current levels of job vacancies and quits.

We then examine the efficacy of the firm-side unemployment rate relative to the actual unemployment rate in predicting wage inflation.

Table 4 presents results from our model regressing the unemployment rate on the log of the vacancy rate and the log of the quits rate[17], using monthly JOLTS data from January 2001 to December 2019. We estimate these models using data from 2001, the first year all four measures of slack are available at the monthly level, through 2019 to avoid changes caused by the Covid-19 pandemic. We run several different model specifications, including different lag lengths, a time trend, and a structural break in July 2009. In general, all the models fit the data very well from 2001 to 2019, but the specifications with more lags, a structural break, and a time trend have the best overall fit[18].

Using these different model specifications, we next predict the out-of-sample unemployment rate past December 2019, given the observed values of the vacancy rate and the quits rate in the monthly JOLTS series. The firm-side predicted unemployment rates for October through December are highlighted in blue at the bottom of the table. We choose to use the model with 12-month lags, a time trend, and a structural break to report results throughout the rest of this paper[19]. For December 2021, this model specification predicts a firm-side equivalent unemployment rate between 1.2 and 1.7 percent, compared to the actual unemployment rate of 3.9 percent, signaling a very tight labor market from the perspective of employers. Using a linear model instead of a linear-log model would lower the estimated firm-side unemployment even further.

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[17] The formalization of the model is presented in Equation 3.

[18] Our results suggest that deviations in the quits rate are more predictive of the unemployment rate than deviations in the vacancy rate. We hypothesize that this can be explained by the outward shift in the Beveridge curve after 2009, which changed the structural relationship between the vacancy rate and the unemployment rate, and made the vacancy rate less predictive.

[19] Given that the vacancy and quits series are nonstationary, and that there is a clear break in the covariance between the vacancy rate and the unemployment rate in 2009, we believe the models that include the time trend and structural break indicator are better fits.

Table 4: Estimating a firm-side equivalent unemployment rate from demand-side slack measures

Dependent variable: Unemployment rate (pp)	w/ 4-month lags				w/ 12-month lags			
	initial model	w/ structural break	w/ time trend	w/ time trend & structural break	initial model	w/ structural break	w/ time trend	w/ time trend & structural break
Log Vacancy rate	-0.39 (0.28)	-2.15*** (0.80)	1.49 (0.96)	-0.22 (1.01)	-0.44 (0.27)	-1.69** (0.81)	-0.020 (1.22)	-0.93 (1.07)
Log Quits rate	-9.10*** (0.42)	-6.63*** (1.08)	-11.2*** (1.09)	-8.61*** (1.24)	-9.42*** (0.38)	-7.63*** (1.17)	-9.88*** (1.33)	-8.34*** (1.29)
After July 2009		0.57** (0.24)		0.79*** (0.22)		0.39 (0.25)		0.50* (0.30)
Time Trend			-0.050** (0.024)	-0.070*** (0.018)			-0.011 (0.032)	-0.029 (0.033)
Constant	11.1*** (0.18)	11.3*** (0.22)	12.6*** (0.71)	13.4*** (0.58)	11.3*** (0.17)	11.4*** (0.18)	11.6*** (0.94)	12.3*** (1.04)
Observations	225	225	225	225	217	217	217	217
Adj R-squared	0.97	0.97	0.97	0.98	0.98	0.98	0.98	0.98
RMSE	0.31	0.29	0.3	0.27	0.27	0.27	0.27	0.27
Predicted Dec Unemployment	1.51 (0.12)	1.33 (0.16)	1.62 (0.14)	1.41 (0.16)	1.44 (0.26)	1.42 (0.26)	1.45 (0.24)	1.45 (0.24)
Predicted Nov Unemployment	1.75 (0.12)	1.48 (0.18)	1.89 (0.14)	1.58 (0.17)	1.60 (0.27)	1.52 (0.28)	1.62 (0.24)	1.56 (0.25)
Predicted Oct Unemployment	1.94 (0.12)	1.60 (0.23)	2.07 (0.13)	1.66 (0.21)	1.70 (0.25)	1.58 (0.27)	1.72 (0.23)	1.60 (0.25)

Notes: Distributed lag regressions show the sum of the coefficients and the corresponding standard errors. The vacancy rate and quits rate data comes from the monthly JOLTS series. Predicted out-of-sample unemployment rates (for the last three months of available JOLTS data) are highlighted in blue. Newey-West standard errors (HAC) in parentheses, *** p<0.01, ** p<0.05, * p<0.1

To compare the predictive power of the firm-side equivalent unemployment rate with the actual unemployment rate for nominal wage growth, we estimate a wage Phillips curve model that includes the actual unemployment rate and our predicted unemployment rate as the regressors[20]. Table 5 displays the results. We run 12 different model specifications, varying the wage series used to calculate nominal wage growth, and changing the lag length of our explanatory variables. The results provide strong evidence that the firm-side equivalent unemployment rate has essentially all the explanatory power in predicting wage inflation compared to the actual

[20] We use the model with 12-month lags, a time trend, and a structural break, and estimate the model from 2001 to 2019.

unemployment rate: across most of our regression specifications, decreases in the firm-side unemployment rate explain nominal wage growth[21]. We also note that this wage inflation usually occurs with either 4-quarter or 8-quarter lags.

Table 5: Wage inflation on firm-side and actual unemployment rates, 2001-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables are 4-quarter MA of YoY % change in wages	CPS-ORG mean wage			CPS-ORG median wage			CES production/nonsupervisory average earnings			Employment Cost Index		
	Contemp	4-quarter lags	8-quarter lags	Contemp	4-quarter lags	8-quarter lags	Contemp	4-quarter lags	8-quarter lags	Contemp	4-quarter lags	8-quarter lags
Firm-side predicted unemployment rate	-0.85 (0.62)	-1.57** (0.66)	-2.89** (1.10)	-0.076 (0.92)	-0.82 (1.14)	-2.19* (1.27)	-1.42*** (0.30)	-1.89*** (0.37)	-1.89*** (0.48)	-0.21 (0.36)	-0.53 (0.40)	-1.52*** (0.37)
Unemployment rate	0.39 (0.60)	1.01 (0.64)	2.32** (1.06)	-0.36 (0.89)	0.33 (1.19)	1.57 (1.22)	1.20*** (0.30)	1.60*** (0.38)	1.54*** (0.46)	-0.059 (0.35)	0.24 (0.39)	1.15*** (0.36)
Weighted lagged inflation	0.34** (0.16)	0.0096 (0.15)	-0.12 (0.13)	0.30** (0.14)	0.039 (0.19)	-0.073 (0.22)	0.62*** (0.099)	0.44*** (0.070)	0.47*** (0.081)	0.28*** (0.059)	0.20*** (0.059)	0.19*** (0.035)
Constant	0.05*** (0.005)	0.06*** (0.006)	0.07*** (0.006)	0.04*** (0.006)	0.05*** (0.006)	0.06*** (0.008)	0.03*** (0.003)	0.04*** (0.002)	0.04*** (0.003)	0.04*** (0.002)	0.04*** (0.002)	0.043*** (0.0019)
Observations	70	66	62	70	66	62	70	66	62	69	66	62
R-squared	0.65	0.75	0.80	0.56	0.64	0.72	0.77	0.89	0.92	0.84	0.88	0.95

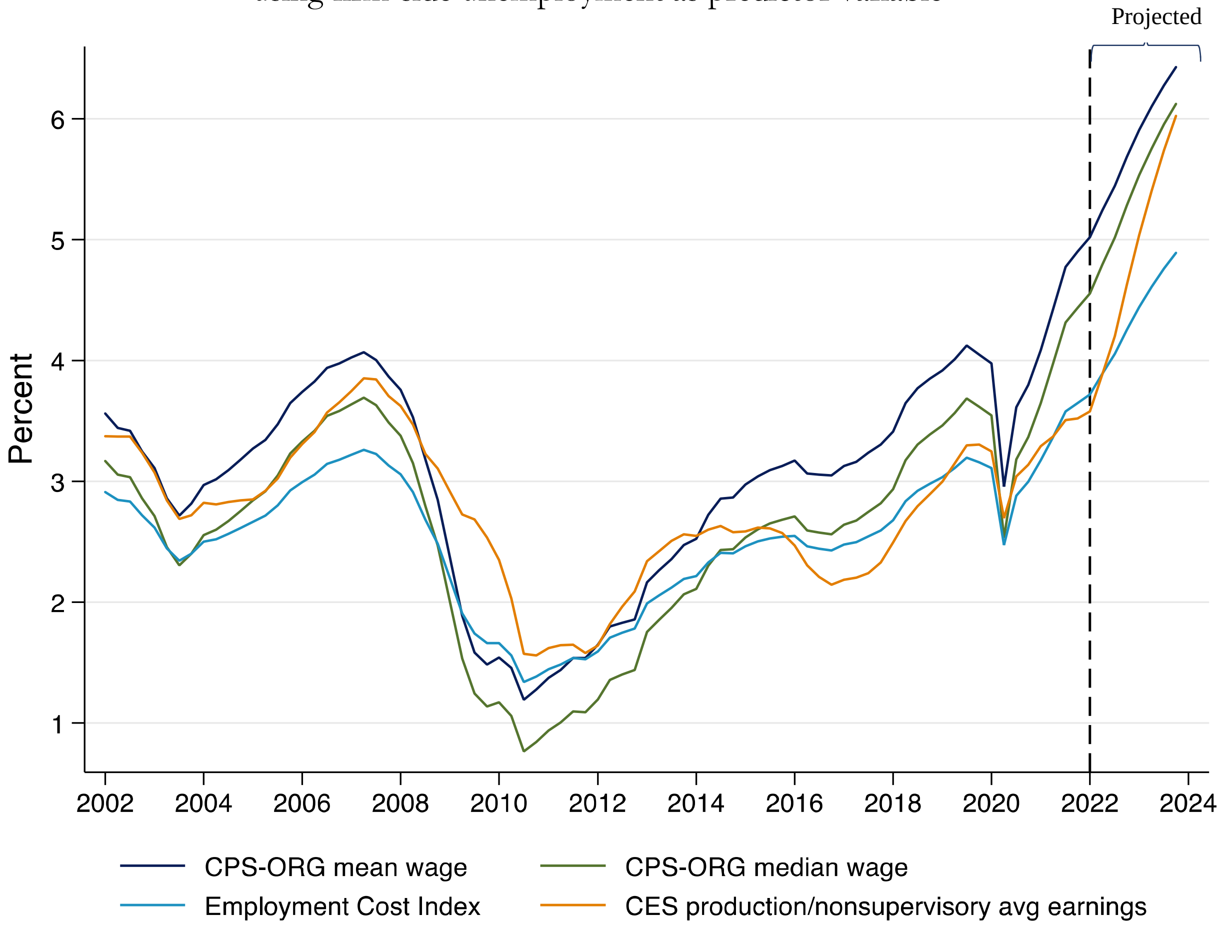
Notes: Distributed lag regressions show the sum of the coefficients and the corresponding standard errors. Newey-West standard errors (HAC) in parentheses with lag order of 5. *** p<0.01, ** p<0.05, * p<0.1

Given the extremely low firm-side predicted unemployment rate today, these results provide strong evidence that the current labor market is very tight. The firm-side predicted unemployment rate has fallen from an average of 3.6 percent in the fourth quarter of 2019 to an average of 1.5 percent in the fourth quarter of 2021, which corresponds to an increase in wage inflation from 4.0% to 4.9% (using CPS-ORG mean wages). Figure 4 below shows estimates for nominal wage growth from a wage Phillips curve model using predicted firm-side unemployment as the slack variable and controlling for lagged inflation. The results indicate that estimated wage inflation in the fourth quarter of 2021 is the highest it's been in the last 20 years across all four of

[21] These results are robust across our other 7 model specifications for predicting the equivalent firm-side unemployment rate.

our wage measures. We then simulate nominal wage growth in 2022 and 2023 under the assumption that the vacancy rate, the quits rate, and the inflation rate remain the same (our 3-year weighted lagged inflation raises to 3% by the end of 2022 and to 5% by the end of 2023). The figure shows that nominal wage growth under these assumptions is projected to increase dramatically over the next two years, surpassing 6% wage inflation by 2023 with three of the four wage measures.

Figure 4: Predicted year-over-year nominal wage growth through 2023, using firm-side unemployment as predictor variable



Notes: We train the model on quarterly data from 2001:Q1 to 2019:Q4 to avoid any structural changes induced by the Covid-19 pandemic. A weighted 3-year lagged inflation variable is included to proxy for expected inflation. All values are seasonally adjusted.
Source: Authors calculations using data from Bureau of Labor Statistics Current Population Survey, (CPS), Employment Cost Index, and Job Openings and Labor Turnover Survey (JOLTS)

3.3 Results from local labor markets

Thus far, we have presented results using aggregate data at the national level. One concern with this approach is that there is limited information available from a single historical time series, particularly since labor market indicators exhibit pro-cyclicality and may be strongly correlated with a number of omitted variables.

To address this concern, we make use of publicly available data at the state-level to investigate whether our findings hold in repeated cross-section data across local labor markets. We use BLS Occupational Employment and Wage Statistics (OEWS) wage data and microdata from the CPS-ORG to compute state-level measures of nominal wage growth, and use BLS data and newly-available JOLTS state-level data to compute state-level estimates for job vacancies, quits, and the unemployment rate[22]. We then estimate wage Phillips curve models to test the relative importance of these slack indicators in predicting wage inflation. Table 6 shows that the state-level wage Phillips curve estimates are broadly corroborative of the aggregate-level results: state-level vacancy and quit rates are highly predictive of wage inflation in models that include the local unemployment rate and lagged regional inflation. These results are robust across different model specifications using moving averages and different lag lengths, as well as across different measures of wage growth (results available upon request).

[22] Prime-age labor force participation data is not available at the state-level, and so is not included in this analysis.

Table 6: Wage inflation on slack indicators using state-level data, 2002-2019[23]

Dependent variables are annual % change in mean OEWS wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment rate	-0.30*** (0.038)	-0.23*** (0.037)	-0.28*** (0.071)	-0.25*** (0.054)	-0.23*** (0.047)	-0.29*** (0.072)	-0.25*** (0.057)	-0.23*** (0.047)	-0.28*** (0.068)
Job vacancy rate	0.12 (0.074)	0.20* (0.11)	0.38*** (0.18)				0.039 (0.065)	0.29* (0.12)	0.41** (0.17)
Quits rate				0.60* (0.33)	0.081 (0.085)	0.19 (0.27)	0.54* (0.32)	-0.13 (0.11)	-0.12 (0.26)
Weighted lagged inflation	0.38*** (0.046)	0.22** (0.097)	0.20* (0.12)	0.31*** (0.047)	0.26*** (0.090)	0.21 (0.12)	0.33*** (0.048)	0.22** (0.095)	0.22* (0.12)
Fixed Effects	State	Year	State, Yr	State	Year	State, Yr	State	Year	State, Yr
Observations	850	850	850	850	850	850	850	850	850
R-squared	0.454	0.576	0.617	0.462	0.574	0.615	0.465	0.579	0.619

Notes: Observations are collapsed to the state-year level to reduce noise of monthly data at the state level. Coefficients are the cumulative effect of the level and one-year lag. Robust standard errors clustered at the state level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We next predict state-level firm-side equivalent unemployment rates, using the same methodology presented in the previous section, and compare the relative efficacy of the firm-side predicted unemployment rates and the actual unemployment rates in explaining historical wage inflation between 2001-2019. Table 7 presents the results from these regressions. The dependent variable is the annual year-over-year change in nominal wages at the state-level. We use four different wage estimates: the OEWS mean and median wages across all occupations, and the composition-adjusted CPS-ORG mean and median wages. We include state and year fixed effects, and also check for robustness across regression specifications that include 4-quarter and 8-quarter lags.

[23] We present results using the mean wages calculated from OEWS hourly wage data, since these models had the highest R-squared. Results are similar across different measures of nominal wage growth.

The results of our state-level regressions corroborate the results found at the aggregate level: in our state fixed effects models, the firm-side predicted unemployment rate is more significant than the actual unemployment rate in predicting wage inflation. When including year fixed effects, and state and year fixed effects, both the unemployment rate and the firm-side unemployment lose their predictive power. These findings are suggestive that the demand-side indicators are likely more significant than the unemployment rate in predicting wage inflation at the state level.

Table 7: Wage inflation on firm-side and actual unemployment rates using state-level data, 2002-2019

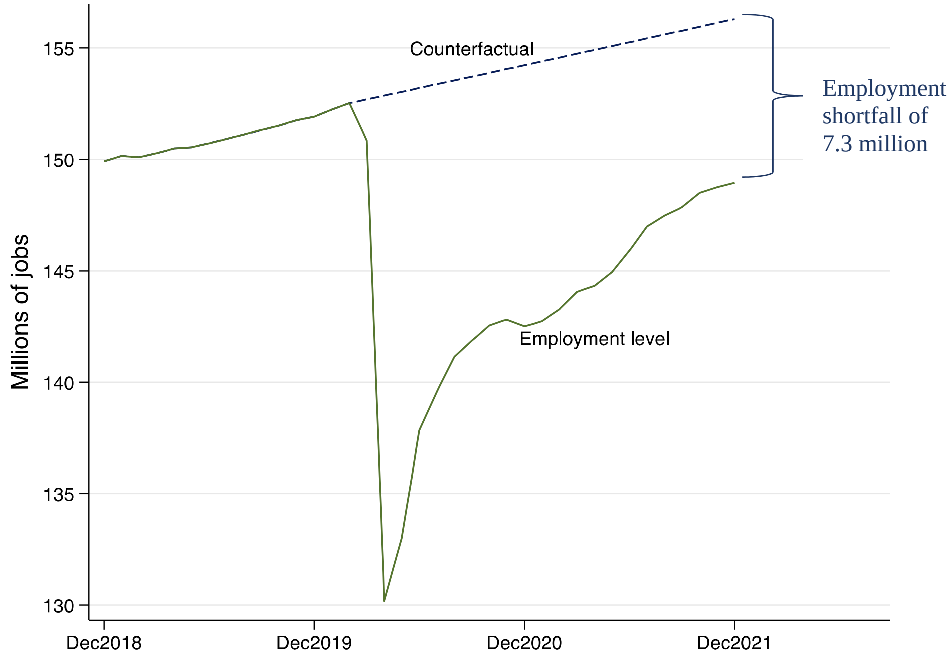
Dependent variables are cumulative dynamic multiplier, annual % change in wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OEWS mean wage			OEWS median wage			CPS-ORG mean wage			CPS-ORG median wage		
Firm-side predicted unemployment rate	-0.42***	-0.049	-0.14	-0.41***	-0.045	-0.13	-0.48**	-0.01	-0.18	-0.52**	-0.055	-0.21
	(0.083)	(0.078)	(0.083)	(0.11)	(0.11)	(0.11)	(0.18)	(0.17)	(0.20)	(0.26)	(0.25)	(0.29)
Unemployment rate	0.14*	-0.13	-0.13	0.028	-0.20	-0.20	-0.024	-0.21	-0.21	-0.036	-0.20	-0.20
	(0.079)	(0.083)	(0.083)	(0.11)	(0.12)	(0.12)	(0.16)	(0.17)	(0.17)	(0.24)	(0.25)	(0.26)
Weighted lagged inflation	0.39***	0.35***	0.27**	0.33***	0.27***	0.21*	0.16	0.069	-0.11	0.13	0.17	0.14
	(0.044)	(0.081)	(0.100)	(0.050)	(0.087)	(0.12)	(0.10)	(0.21)	(0.26)	(0.10)	(0.19)	(0.25)
Fixed Effects	State	Year	State, Yr	State	Year	State, Yr	State	Year	State, Yr	State	Year	State, Yr
Observations	850	850	850	850	850	850	850	850	850	850	850	850
R-squared	0.400	0.575	0.617	0.465	0.573	0.615	0.130	0.172	0.188	0.128	0.133	0.148

Notes: Observations are collapsed to the state-year level to reduce noise of monthly data at the state level. Regressions include 50 states x 17 years (850) observations. Coefficients are the cumulative effect of the level and one-year lag. Robust standard errors clustered at the state level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4 Labor Supply Estimates Going Forward

The evidence we have presented in this paper suggests that the labor market is currently extremely tight – the elevated job vacancy and quits rates imply that the labor market has a degree of tightness that would historically have been associated with an aggregate unemployment rate below 2 percent. How can this conclusion be squared with the observation that employment levels remain well below the pre-Covid trend, as illustrated in Figure 5?

Figure 5: Employment shortfall relative to pre-pandemic trend

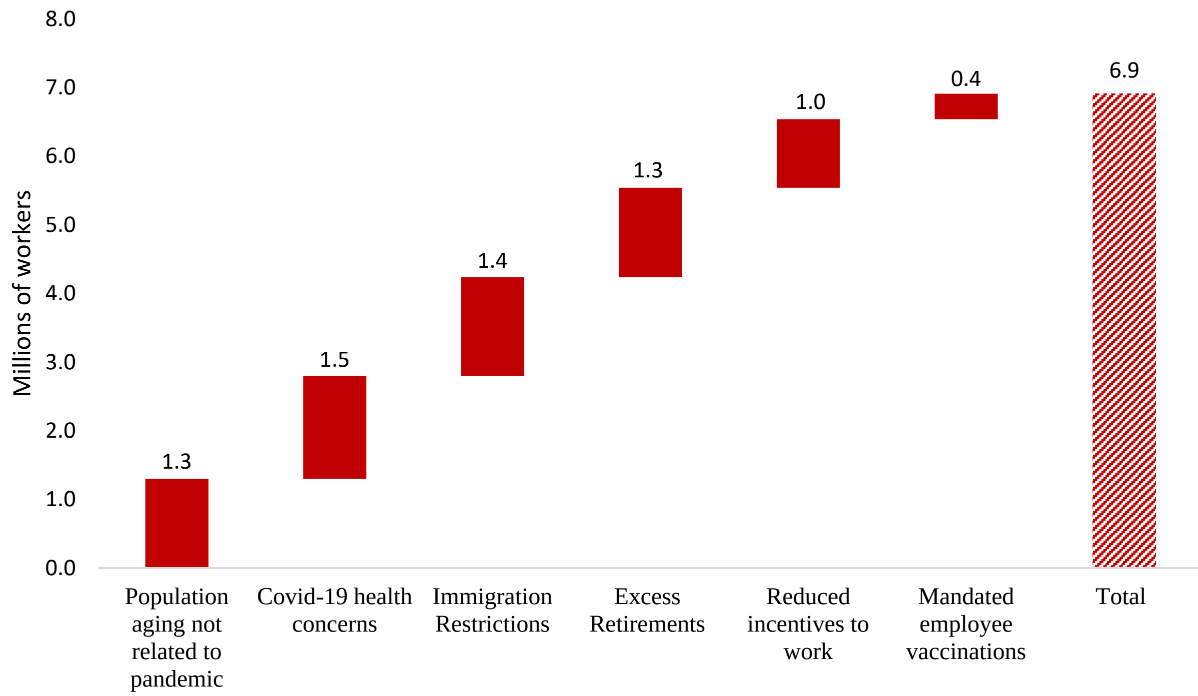


Notes: Employment is nonfarm payroll employment, which excludes proprietors, self-employed, unpaid family or volunteer workers, farm workers, and cosmetic workers. Counterfactual employment level assumes employment continued to grow at the 2019 rate. Results are similar if a 3- or 5-year pre-pandemic trend is used instead.
Source: Authors calculations using data from Bureau of Labor Statistics Current Population Survey, (CPS).

Economists have suggested a number of reasons to explain the current employment shortfall, including non-pandemic related shifts in the age structure of the labor force, a surge in early retirements, immigration restrictions, lingering health risks from Covid-19, and a variety of factors that have reduced the incentive to work and increased workers' reservation wages. We present a cursory analysis below of these different factors contributing to the employment shortfall, and conclude that most of the factors reducing employment are not likely to be rapidly reversed, even with relatively favorable Covid-19 outcomes.

Figure 6 displays our rough breakdown of the relative contribution of different factors to the employment shortfall. Overall, we estimate that most of the employment shortfall will remain through 2022, with Covid-19 health concerns, immigration restrictions, excess retirements, shifts in workers' tastes, and changes in the demographic structure explaining the bulk of the labor shortfall.

Figure 6: Estimated shortfall in labor facing employers in 2022, relative to Feb 2020



Source: Authors' calculations.

In the rest of this section, we explain the different factors contributing to the employment shortfall, and provide a cursory attempt to quantify the magnitude of each of these factors over the coming year.

Shifts in Demographic Structure – 1.3 million workers

Population aging unrelated to the pandemic will continue to have a pronounced effect on labor force participation over the coming year. Furman and Powell (2021) estimate that the changing age-sex structure of the population decreased labor force participation by 0.5 percentage points between February 2020 and November 2021, corresponding to about 825,000 workers. Extrapolating these estimates to 2022, we project an additional 0.3 percentage point decrease in labor force participation in 2022 due to population aging, corresponding to a contraction of 500,000 more workers from the labor force.

Covid-19 Health Concerns – 1.5 million workers

Elevated health concerns related to Covid-19 will likely continue to have a negative effect on labor supply over the subsequent year. Our estimate of 1.5 million workers is based on a variety of data sources. First, using available estimates on the percentage of immunocompromised people by age group from Harpaz et al. (2016), we estimate that between 4.3 to 5.7 million working age adults are immunocompromised– suggesting elevated health concerns will remain for a substantial portion of the working-age population. Second, the latest Census Bureau Household Pulse Survey from December 29 to January 10 estimates that 3.2 million workers were not at work in the previous week due to Covid-19 health concerns. This number has remained relatively constant over the last 6 months. Third, recent studies have shown that many of the symptoms of Covid-19 can linger long after an infection. While estimates of the prevalence of long Covid-19 symptoms range wildly, the Office for National Statistics in the U.K. estimates that the rate of long-term Covid-19 infections is around 5 percent of people (Antonelli et al, 2021). Another Lancet study found that 22% of individuals with long Covid-19 symptoms were not working due to their health condition (Davis et al, 2021). Given these estimates, the emergence of the Omicron variant, and the stagnating vaccination rates among U.S. adults, we believe it is plausible that Covid-19 health concerns continue to reduce employment by around 1.5 million workers in 2022.

Immigration Restrictions – 1.4 million workers

In 2020 and 2021, the number of immigrants arriving in the United States dropped substantially, due to increased restrictions related to the Covid-19 pandemic. According to data from the Current Population Survey, prior to 2019 the foreign-born population of working age grew at an average rate of about 660,000 people year. Since the pandemic, there has been effectively zero growth in the working-age foreign born population. Peri and Zaiour (2022)[24] use data from the CPS and Department of State and find that the number of working-age foreign-born people in the United States by the end of 2021 is 2 million people below the 2010-2019 trend. We apply a foreign-born working-age employment rate of 72% (OECD, 2022), and estimate a shortfall in employment of 1.4 million workers due to immigration restrictions.

Excess Retirements – 1.3 million workers

At the beginning of the Covid-19 pandemic, there was a large spike in the share of the U.S. population (age 16 and above) that was retired. We compare the actual number of retirees to the expected number of retirees implied by the age-specific retirement rates observed in 2019, [25] and find that there were 1.3 million excess retirements between February 2020 and Dec 2021[26]. This estimate is consistent with estimates from several other recent models attempting to quantify the labor shortfall due to excess retirements[27]. Given that this number has been relatively constant since mid-2020, we believe it is unlikely that the number of excess retirees will decline over the subsequent year.

Reduced Incentives to Work – 1 million workers

According to data from the Federal Reserve Bank of New York's SCE labor market survey, the average reservation wage increased by 9.3% between Nov 2019 and Nov 2021[28]. This increase in the reservation wage can be explained by many factors that have reduced the marginal cost of continued search, including government transfers like the child tax credit, an increase in home

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[24] Giovanni Peri and Reem Zaiour, "Labor Shortages and the Immigration Shortfall." Jan 2022. https://econofact.org/labor-shortages-and-the-immigration-shortfall

[25] This follows the methodology used in Briggs et al. "Will Worker Shortages Be Short-Lived?" Goldman Sachs Global Investment Research. October 2021

[26] This estimate is a 3-month moving average. The projected number of excess retirees is similar when using the age-specific retirement rates observed from 2017-2019, rather than just 2019.

[27] See Briggs et al. "Will Worker Shortages Be Short-Lived?" Goldman Sachs Global Investment Research. October 2021; Nie and Yang (2021) and Faria-e-Castro (2021)

[28] See New York Fed SCE Labor Market Survey results at https://www.newyorkfed.org/microeconomics/sce/labor#/

values and personal savings, and a shift in work-life preferences during the pandemic. We present evidence on these factors in turn.

The American Rescue Plan expanded the child tax credit to a total of $3,600 for children 5 and younger (up from $2,000 per child), and $3,000 for those ages 6 through 17, and made the full credit available to all low and middle-income families regardless of earnings or income. Relying on elasticity estimates consistent with the academic literature, Corinth et al. (2021) estimates that the expanded child tax credit would cause 1.46 million workers to leave the labor force[29]. While negotiations to continue the expanded Child Tax Credit in 2022 have stalled, we believe it is reasonable that a share of the Corinth et al. (2021) estimate has already materialized, pushing up workers' reservation wages.

An increase in personal savings and property values is also responsible for keeping workers out of employment. Through September 2021, the typical low-income family still had 70 percent more cash on hand than two years prior[30], while in November 2021, about 25% of the unemployed reported that they were not urgently searching for a job due to large financial cushion[31]. Most estimates for the total excess savings accumulated in the United States since the beginning of the pandemic are around $2.5 trillion[32]. Home values have also appreciated dramatically, hitting a peak year-over year increase of 19.3 percent in July 2021[33][34].

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[29] Corinth et al (2021) estimate that workers with earnings below $50,000 account for 72% of the employment loss, while workers with earnings above $50,000 account for 28% of the employment loss. We attribute the full labor supply shock of this policy to take effect by the end of 2022 – though it is possible the effects will be more long-term.

[30] JPMorgan Chase, Household Cash Balance Pulse: Family Edition, November 2021

[31] Indeed Hiring Lab Job Search Survey, November 2021

[32] See JP Morgan Chase, "Quick shot: Consumers' cup runneth over." Oct 7, 2021; *The Economist,* "Will Americans pandemic savings stash keep the economy rolling?" Jan 15, 2022

[33] John Duca and Anthony Murphy (2021), "Why House Prices Surged as the Covid-19 Pandemic Took Hold." Federal Reserve Bank of Dallas, Dec 2021.

[34] Homeowners are also more likely than renters to leave the labor force during an economic downturn: Asquith, B. (2021) finds that job displacements form the Great Recession caused an 8% decrease in labor force participation among renters and a 16% decline among homeowners.

Finally, there is also substantial evidence that workers' work-life preferences have shifted during the Covid-19 pandemic. The Pulse of the American Worker Survey conducted by Prudential Morning-Consult (2021) found that 48 percent of US workers are rethinking the type of job they want post-pandemic, and 26% say that a desire to work remotely at least some of the time is fueling their desire to switch jobs. A survey by Bloomberg (2021) found that 39 percent of employees would consider quitting if they couldn't work from home, while a McKinsey and Company study (Alexander et al. 2021) found that 28 percent of US workers in corporate or government settings are likely or very likely to quit if they are required to go back to full-time work in person.

Taken together, these factors driving up reservation wages are likely to continue to significantly impact labor supply over the coming year.

Covid-19 Vaccine Mandates – 0.4 million workers

As of November 2021, 29 percent of workers say their employer has enforced a vaccine mandate (KFF Covid-19 Vaccine Monitor, November 8-22). A survey by the Kaiser Family Foundation also found that 4 percent of unvaccinated workers have personally left their job because their employer required them to get a Covid-19 vaccine. Assuming these numbers remain constant in 2022, we estimate that 0.4 million workers will leave their jobs due to Covid-19 vaccine mandates[35].

Labor demand estimates

In total, our estimates suggest that a substantial portion of the employment shortfall will likely persist throughout 2022. At the same time, we project demand-side indicators such as the vacancy to unemployment ratio to continue to be very high over the next year. Table 8 shows estimates for

[35] This estimate assumes there are 40 million unvaccinated US adults (CDC data) and an employment ratio of 78.8%.

the v/u ratio in June 2022 under different assumptions for the trajectory of unemployment, labor force participation, and job vacancies. Even in the most optimistic scenarios, Table 8 implies that the v/u ratio will continue to be extraordinarily high over the next six months, implying significant inflationary pressures from the labor market in 2022[36].

Table 8: Projected vacancy to unemployment ratio in June 2022 under different scenarios

Unemployment rate in June 2022	**Monthly change in LFPR**	**Rate of new vacancies/new labor force entrants**	**Estimated vacancy/unemployment ratio in June 2022**
3.5%	No change	0%	1.81
3.5%	Increases at 2021 rate	0%	1.67
3.5%	Increases at 2021 rate	25%	1.71
3.5%	Increases at 2021 rate	50%	1.74
3.5%	Increases at 2021 rate	100%	1.81
3.5%	Increases at 2021 rate	200%	1.94
4%	No change	0%	1.71
4%	Increases at 2021 rate	0%	1.59
4%	Increases at 2021 rate	25%	1.62
4%	Increases at 2021 rate	50%	1.65
4%	Increases at 2021 rate	100%	1.71
4%	Increases at 2021 rate	200%	1.83
3%	No change	0%	1.94
3%	Increases at 2021 rate	0%	1.78
3%	Increases at 2021 rate	25%	1.82
3%	Increases at 2021 rate	50%	1.86
3%	Increases at 2021 rate	100%	1.94
3%	Increases at 2021 rate	200%	2.1

Notes: The baseline case assumes no change in labor force participation and that vacancies reduce one for one with decreases in unemployment. For the other cases, we assume that labor force participation increases at the same monthly rate experienced throughout 2021, and that all the increases in labor force participation go directly to reducing vacancies (i.e. all transitions from not in the labor force go directly into employment).
Source: Bureau of Labor Statistics Current Population Survey (CPS) and Job Openings and Labor Turnover Survey (JOLTS) via FRED, authors' calculations.

[36] Using historical data, we estimate that the average rate of new vacancies to new labor force entrants is about 2:1. This would imply a v/u ratio of 1.94 with a 3.5% unemployment rate, a v/u ratio of 1.83 with a 4.0% unemployment rate, and a v/u ratio of 2.1 with a 3.0% unemployment rate.

5 Conclusion – Labor Market Tightness Moving Forward

In recent months, different labor market indicators have signaled varying degrees of slack left in the U.S. labor market. While some supply-side indicators, such as the unemployment rate and the prime-age employment rate, indicate modest degrees of slack, the demand-side indicators, such as the job vacancy rate and the quits rate, suggest a very tight labor market. The results presented in this paper suggest that the firm-side indicators are highly significant for predicting wage inflation, and that the current level of vacancies and quits observed in the labor market correspond to a degree of labor market tightness previously associated with unemployment rates below 2 percent. We also show that firm-side unemployment predicts extremely rapid growth in nominal wages over the subsequent year. Overall, the evidence presented in this paper indicates that U.S. labor markets are currently extremely tight.

Some economists believe that labor market tightness will be alleviated over the coming year by increases in labor supply. We present a cursory analysis of the employment shortfall, and conclude that even under optimistic Covid-19 outcomes, the majority of the employment shortfall will likely persist moving forward. Moreover, if employment were to increase due to an increase in labor force participation, it would be accompanied by increases in incomes, and therefore an increase in demand. We therefore conclude that any benefits from the supply-side over the next year are unlikely to substantially mitigate inflation pressures from the labor market. Given these estimates, and the results presented throughout the rest of this paper, we believe that labor markets will continue to be very tight unless there is a considerable slowdown in labor demand. Overall, these findings suggest to us the need for substantial caution about the possibility of inflationary pressures from the labor market moving forward.

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