A Theory of How Workers Keep Up With Inflation*

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December 2024

Abstract

In this paper, we develop a model that combines elements of modern macro labor theories with nominal wage rigidities to study the consequences of unexpected inflation on the labor market. The slow and costly adjustment of real wages within a match after a burst of inflation incentivizes workers to engage in job-to-job transitions. Such dynamics after a surge in inflation lead to a rise in aggregate vacancies relative to unemployment, associating a seemingly *tight* labor market with *lower* average real wages. Calibrating with pre-2020 data, we show the model can simultaneously match the trends in worker flows and wage changes during the 2021-2024 period. Using historical data, we further show that prior periods of high inflation were also associated with an increase in vacancies and an upward shift in the Beveridge curve. Finally, we show that other "hot labor market" theories that can cause an increase in the aggregate vacancy-to-unemployment rate have implications that are inconsistent with the worker flows and wage dynamics observed during the recent inflationary period. Collectively, our calibrated model implies that the recent inflation in the United States, all else equal, reduced the welfare of workers through real wage declines and other costly actions, providing a model-driven reason why workers report they dislike inflation.

JEL Codes: E24, E31, J31, J63
Key Words: Inflation, Vacancies, Job-to-Job Flows, Beveridge Curve, Wage Growth

*We thank Yash Singh for his outstanding research assistance and Guido Lorenzoni, Gabe Chodorow-Reich and Joe Hazell for providing us with helpful comments. We also thank seminar participants at Chicago, Columbia, Harvard, LSE, Michigan, UCLA Anderson, the Federal Reserve Board, the Federal Reserve Bank of Atlanta, the 2024 Society of Economic Dynamics conference, the 2024 NBER Macroeconomics over Time and Space conference, the 2024 NBER Monetary Economics Fall meeting, and the 2024 St. Louis Fed-Washington University Macro Labor conference for helpful comments. The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve Board. Email: hassan.afrouzi@columbia.edu; julio.blanco@atl.frb.org; andres.drenik@austin.utexas.edu; and erik.hurst@chicagobooth.edu.

Online Appendix

A Data Description

In this section of the appendix, we discuss in detail the data work we use in the paper.

A.1. JOLTS

We use the Job Openings and Labor Turnover Survey (JOLTS) data to measure quits, layoffs, and vacancies during the December 2001 through the June 2024 period. We downloaded the data directly from the JOLTS data website when creating the descriptive work shown in Section 2.[39] The JOLTS dataset, collected by the U.S. Bureau of Labor Statistics (BLS) provides a snapshot of worker hiring and separation flows for a nationally representative sample of non-farm business and government employers during a given month. Below, we provide definitions of the JOLTS Layoff Rate, Quit Rate, and Vacancy Rate.

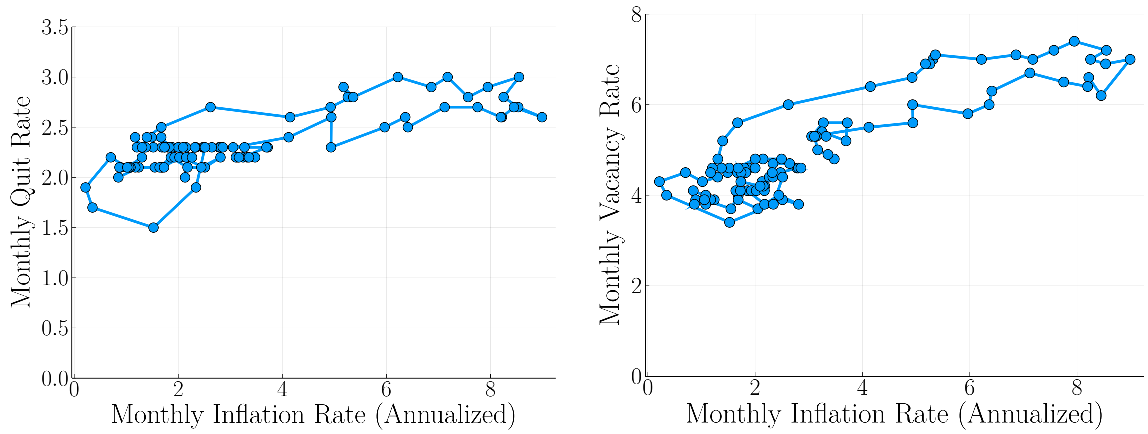
Layoff Rate: The *layoff rate* reflects all workers who were involuntarily terminated by a firm during a given month divided by total monthly employment. Involuntary terminations include workers laid-off with no intent to rehire; workers fired or discharged for cause; workers whose discharge resulted from mergers, downsizing, or firm closings; and seasonal workers discharged at the end of the season.

Quit Rate: The *quit rate* reflects workers who left voluntarily during the month divided by total employment at the end of the month. The quit rate captures workers who left the firm by either (i) flowing into unemployment before starting to look for another job (a voluntary "E-U" flow), (ii) directly transitioning to another firm (an "E-E" flow), or (iii) leaving the labor force (an "E-N" flow). Panel A of Appendix Figure A.1 highlights the close relationship between the monthly CPI inflation rate and the monthly quit rate during this period. Each observation in the figure is a month during the 2016 to 2024 period. As seen from Panel A, there is a strong positive relationship between monthly year-over-year price inflation and the monthly quit rate. A simple linear regression through the scatter plot finds that a 1 percentage point increase in the inflation rate is associated with a 0.103 percentage point increase in the quit rate (standard error = 0.007); the R-squared of the regression was 0.70.

Vacancy Rate: The *vacancy rate* (or job-opening rate) is the number of open positions on the last business day of the month divided by the sum of employment and vacancies on the last day of the month. This data was also used when making the vacancy-to-unemployment rate series shown in Panel A of Figure 1. Panel B of Appendix Figure A.1 shows the tight relationship between the year-over-year CPI inflation rate and the monthly vacancy rate over

[39] See, https://www.bls.gov/jlt/data.htm.

Figure A.1: Monthly Inflation vs Monthly Labor Market Flows



Panel A: Quit Rate vs. Inflation Rate

Panel B: Vacancy Rate vs. Inflation Rate

Notes: Figure shows a scatter plot of the year-over-year CPI inflation rate vs the monthly quit rate (Panel A) and the monthly vacancy rate (Panel B). Each observation is a month between January 2016 and May 2024. The quit and vacancy rates are obtained from JOLTS while the inflation numbers are from the BLS'S CPI for urban consumers.

the entirety of the 2016 to 2024 period. This figure is analogous to the Beveridge curve but with the price inflation rate on the x-axis instead of the unemployment rate. While there has been a well-documented breakdown of the Beveridge curve during the last few years, the relationship between the inflation rate and the vacancy rate remained relatively stable during this time period. In particular, a simple linear regression through the scatter plot finds that a 1 percentage point increase in the inflation rate is associated with a 0.438 percentage point increase in the vacancy rate (standard error = 0.020); the R-squared of the regression was 0.83.

A.2. Atlanta Fed Wage Tracker

For our descriptive work on real wage growth during the 2016-2024 period, we use data from the Atlanta Fed Wage Tracker Index.[40] The Wage Tracker Index uses the panel component of the Current Population Survey (CPS) to make a measure of composition adjusted nominal wage growth. The structure of the CPS is such that individuals are in the sample for four months where they are surveyed about their labor market activities. After that, they leave the sample for eight months and then re-enter for a final four additional months. In their fourth

[40] We downloaded the data directly from https://www.atlantafed.org/chcs/wage-growth-tracker.

survey month and their eight survey month - which takes place one year apart - individuals are asked about their wages. The Atlanta Fed Wage tracker measures a year-over-year change in the workers per-hour nominal wage on their main job. For salaried workers, the hourly wage is computed as weekly earnings divided by usual weekly hours worked.

A.3. CPS Monthly Files

We use the Outgoing Rotation Group (ORG) of the Current Population Survey (CPS) to make our own measures of worker flows and wage dynamics across workers with different earnings. These moments are used to calibrate the worker heterogeneity within our model. In particular, we leverage this short panel to observe individual labor market flows by skill level (education) and initial earnings decile. Sample selection and estimation of labor market flows and earnings are described below.

A.3.1. Sample Selection. For the years 2015 to 2024, we select all individuals from ages 25 to 55, inclusive. We exclude all government employees, self-employed workers, and unpaid family members. This leaves us with 4,077,904 worker-month observations. This is the main sample we use in all the subsequent analyses.

A.3.2. Measure of Earnings. As noted above, in months 4 and 8 of the CPS interview waves, all employed workers in the week of the survey are asked about their usual weekly earnings. We use full-time workers' reported nominal weekly earnings as our wage measure. The CPS top codes individuals with nominal weekly earnings of higher than 2884 U.S. dollars. This top coding procedure changed in April 2023. To maintain consistency throughout our sample, we top code all workers with earnings of more than 2880 nominal U.S. dollars. Each month, we use the associated price index (CPI-U) published by the BLS to convert nominal earnings to real and create a cross-sectional real earnings distribution over time.

A.3.3. Labor Market Flows. The CPS basic monthly files report the employment status - employed or unemployed - of each individual in the labor force. We directly observe changes in employment status for each individual across adjacent months which provides us with a measure of gross flows from employment to unemployment (EU) and unemployment to employment (UE). In addition, we also observe a change in employers across adjacent months which allows us to measure EE flows. There are several technical issues that warrant discussion here. Fujita, Moscarini, and Postel-Vinay (2024) show that the CPS systematically underestimates EE flows since 2007 due to changes in survey methodology which induce selection on both unobservable and observable worker characteristics that are correlated with EE transitions. We use their published aggregate EE series to discipline our EE rates by earnings deciles and education group. Our raw EE estimates by various groups underestimate true EE flows, so we use a constant scaling factor to scale our EE flows by deciles to hit the aggregate EE rate as calculated by Fujita, Moscarini, and Postel-Vinay (2024). We use the following equation to determine our scaling factor:

$$EE = \frac{\alpha}{10}\sum_{d=1}^{10} EE_d \tag{A.1}$$

The decision of a constant scaling factor across deciles warrants discussion. If the elasticity of E-E probability varies with earnings then the scaling factor should be different. According to both Autor, Dube, and McGrew (2024) and our model, returns to search effort, in expectations, are decreasing in current earnings. Therefore, search effort, and in turn, EE rates are more elastic at the bottom of the earnings distribution which implies that a constant scaling factor underestimates the true EE rate for low earners and overestimates EE rates for high earners. Thus, our estimates which show that EE rates increased more for low earners relative to high earners is a conservative lower bound. Similar issues persist with estimating EU and UE flows using microdata in the CPS. We follow the seminal work of Shimer (2005) to infer the EU and UE using aggregate gross worker flows. Of course, data is observed in discrete time at a monthly frequency so we estimate the job finding rate (UE rate) by:

$$\lambda_t = 1 - \frac{U_{t+1} - U^s_{t+1}}{U_t} \tag{A.2}$$

where U represents the stock of unemployed workers at a given point in time and U^s represents the stock of short-term unemployed workers (unemployed for $<=$ 4 weeks). The separation rate (EU) rate is estimated using:

$$\delta_t = \frac{U^s_{t+1}}{E_t(1 - \frac{1}{2}\lambda_t)} \tag{A.3}$$

where E is the stock of employed workers at a given point in time.

B Additional Descriptive Results

In this section of the appendix, we show additional results as referenced throughout the main paper.

B.1. Evolution of Real Wages

We begin by showing that the real wage dynamics during the inflation period shown in Figures 1 and 4 are robust to alternative assumed real wage trends. In the main text, we constructed counterfactual real wages assuming they evolved according to the real wage trends during the pre-inflation ($2016-2019$) period. Figure B.1 shows that roughly similar gaps between expected and realized real wages emerge if we use the longer $2000-2019$ period to define our pre-period trend. These patterns are shown across the five panels in Figure B.1. In June 2024, nearly all groups remain below trend - with the median worker still 3.4% below their expected wage. The bottom income quartile, however, is now slightly above their expected wage in June 2024 when using the longer period to calculate the predicted trend; the trend in real wages for the bottom quartile worker was lower during the $2000-2019$ period than it was during the $2016-2019$ period.

B.2. Dynamics of Unemployment

Figure B.2 shows that the decline of unemployment starting in 2021 was largely driven by declining job destruction rate (or layoffs) rather than increasing job finding rate. We show that the decline in job destruction rates predicted by our theory are largely responsible for the unemployment dynamics since 2021. To see this easily, observe that if fluctuation in job-finding (red) explained all of the variation in unemployment (black) then the the two lines would be perfectly on top of each other, but clearly this is not the case. The fluctuations in job-finding predict persistently higher unemployment than what is observed. Changes in job destruction rate closely track the dynamics of unemployment during this period. This is a unique feature of labor market flows during the $2021-2024$ inflation period as Shimer (2012) finds that job-finding (rather than job-destruction) explains 80% of the variation in unemployment since 1948 in the US data. These results are consistent with the fact that the U-E rate did not change much during the inflation period; instead it was the decline in layoffs that were driving unemployment dynamics.

B.3. Duration of Vacancy

B.3 shows that the average time to fill a vacancy rose from about 30 days in the pre-period to 45 days during the peak of inflation. We use data on hires and vacancies at a monthly frequency from JOLTS to estimate the job-filling rate and back out the expected duration to fill a vacancy. Following the methodology described in Davis, Faberman, and Haltiwanger (2013), we assume that hires on day s of month t is given by:

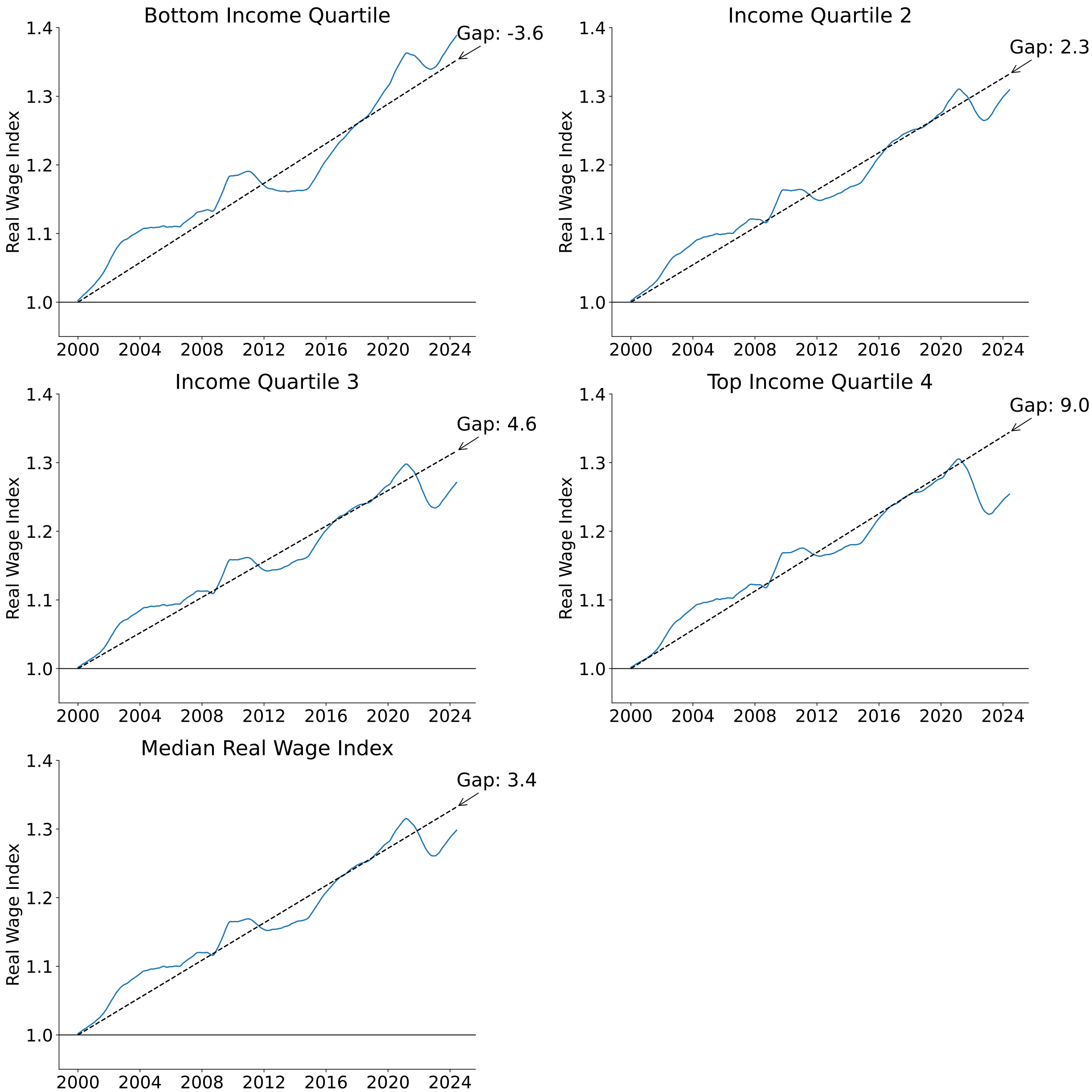
$$h_{s,t} = f_t v_{s-1,t} \tag{B.1}$$

f_t is the daily job-filling rate which is constant over a given month, and $v_{s-1,t}$ is the stock of vacancies on day $s-1$ of month t. The above equations implies that a constant fraction f_t of vacancies are filled by new hires each day. Since data is reported at a monthly frequency, let $H_t = \sum_{s=1}^{26} h_{s,t}$. Then, in the steady state, the daily job-filling rate is given by:

$$f = \frac{H}{v}\left(\frac{1}{\tau}\right) \tag{B.2}$$

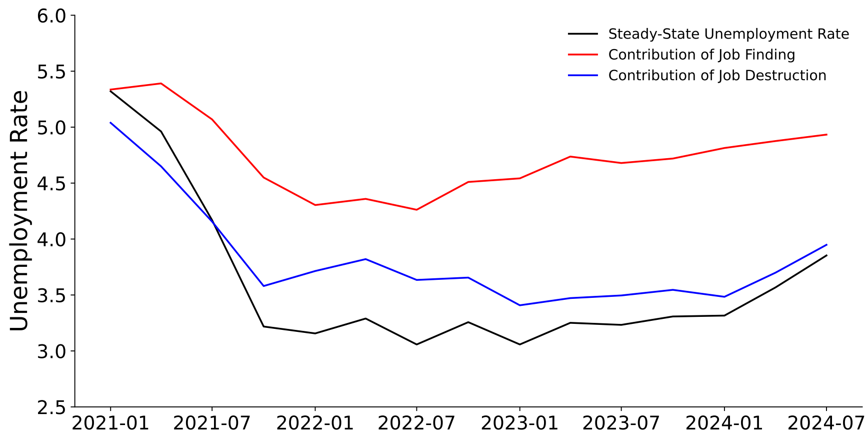
$\tau = 26$ represents the number of working days in a month. Given monthly data on hires and vacancies, the job-filling rate f_t can be directly estimated. The duration of a vacancy, in expectation, is given by $\frac{1}{f_t}$, the object of B.3.

Figure B.1: Evolution of Real Wages



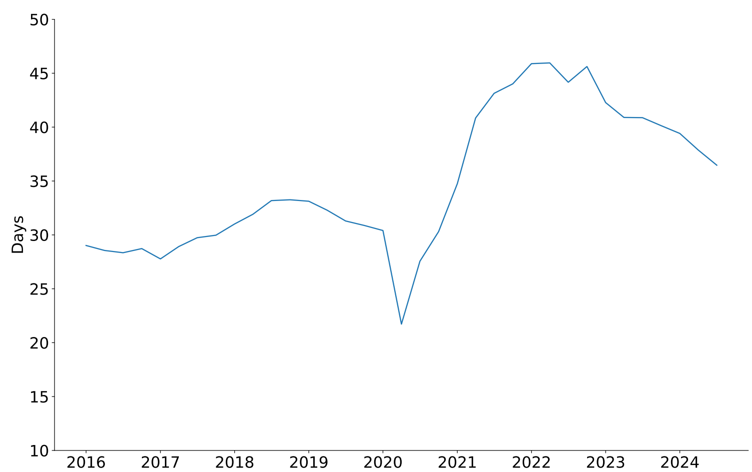
Notes: This figure shows the evolution of real wages across the income distribution between 2000 and 2024 for the same gropus shown in panel B of Figure 1 and in all panels of Figure 4. The blue line indicates realized real wages and the dotted black line shows the trend in real wage. The trend in wages is recovered separately for each group on wage data between 2000 – 2019. We project this trend on 2020 – 2024 data to create a counterfactual wage gap between predicted and observed real wage for each income group in June of 2024. The data is directly taken from Atlanta Fed Wage tracker.

Figure B.2: Decomposition of Unemployment Dynamics



Notes: Contribution of fluctuations in the job finding (UE) and job destruction (EU) rates to fluctuation in the unemployment rate, 2021-2024, quarterly average of monthly data. The red line shows the counterfactual unemployment rate if all fluctuation were due to changes in the job finding rate ($\frac{\bar{\delta}}{\bar{\delta}+\lambda_t}$) and the blue line shows the counterfactual unemployment rate with only fluctuations in the job destruction rate ($\frac{\delta_t}{\delta_t+\bar{\lambda}}$). $\bar{\delta}$ and $\bar{\lambda}$ is the average job destruction and job finding rate between 1990 and 2024. The black line is the implied steady state unemployment rate ($\frac{\delta_t}{\delta_t+\lambda_t}$). This is a good approximation to the observed unemployment rate - correlation of .95 over $1990-2024$.

Figure B.3: Duration of Vacancy

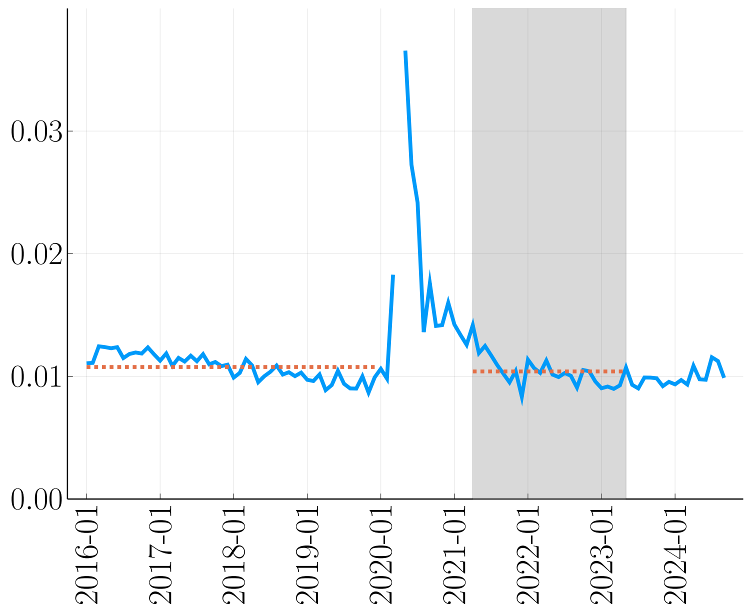


Notes: We estimate the job-filling rate given the data on the flow of hires and the stock of vacancies (see Davis, Faberman, and Haltiwanger (2013) for details). We take a quarterly average of the monthly job-filling rate and plot plot the implied duration of a vacancy.

B.4. E-U Flows, CPS Data

In this section, we show the E-U rate from the CPS. In particular, we downloaded the series "labor force flows employed to unemployed" and "all employees, total nonfarm" directly from the St. Louis Federal Reserves Economic Database (FRED) who extracted the series from CPS aggregates published by the BLS to make the E-U rate. For readability, we exclude the data from April 2020 from the graph when the EU rate exceeded 13%. As seen from the figure, the E-U rate did not change at all during the inflation period relative to the pre-period. All of the documented quits from the JOLTS data are showing up as increased E-E churn.

Figure B.4: E-U, CPS Data



Notes: Figure shows the monthly E-U rate during the 2016-2024 period. Data downloaded directly from the St. Louis Federal Reserves Economic Database (FRED). In particular, we downloaded their series "labor force flows employed to unemployed" and "all employees, total nonfarm" to make the E-U rate. For readability, we exclude the data from April 2020 from the graph when the EU rate exceeded 13%.

B.5. E-E Flows, By Education Group

Appendix Table B.1 shows the change in the E-E rate during the pre-inflation period and the September 2021 through December 2022 period by education group.[41] We use education group as a proxy for the individual's position in the income distribution. These data are the same as we used for the aggregate E-E rate series in the main paper. The figure documents that the change in the E-E rate was not constant throughout the income distribution. Lower educated (lower income) individuals had a much larger change in the E-E rate (0.23 percentage points) than did higher educated (higher income) individuals (0.11 percentage points).

[41]We highlight the change in the E-E rate during a subset of the inflation period given that, as seen in Figure 3, this is the period when E-E rates were the highest.

Table B.1: Change in E-E Flows by Education during Inflation Period

Education	2016M1-2019M12	2021M9-2022M12	Change
Less than Bachelors	2.34%	2.57%	0.23 p.p. (0.04)
Bachelors or More	2.22%	2.33%	0.11 p.p. (0.05)

Notes: The table shows the average E-E rate for individuals with less than a Bachelor's degree (top row) and individuals with a Bachelor's degree or more (bottom row) during the inflation pre-period (column 1) and then again during the September 2021 through December 2022 period (column 2). Column three shows the difference in E-E rates between the two periods with the standard error of the difference in parentheses. The sample is restricted to those aged 25-55 from the monthly CPS files.

B.6. Job-Stayers vs Job-Changer Wage Growth, Atlanta Fed

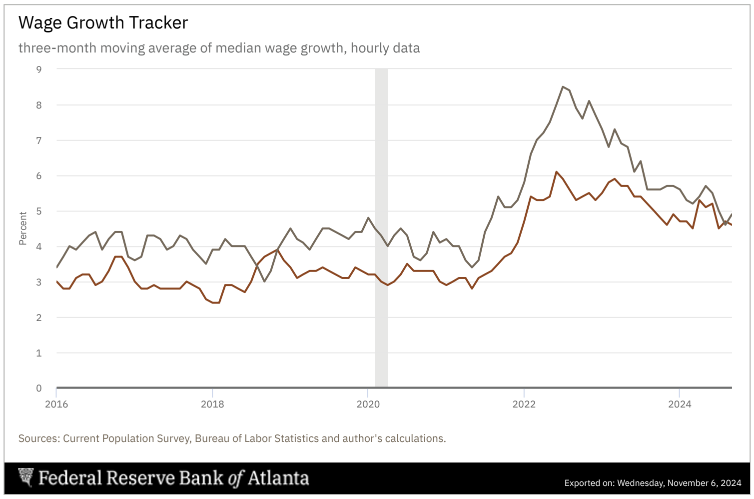
The Atlanta Fed Wage Tracker Index also measures the nominal wage growth of job-stayers relative to job-changers over time. The underlying data for the Atlanta Fed Wage Tracker comes from the CPS. A key limitation of using the CPS data to measure the wage growth of job-changers is that the CPS follows addresses not people. If someone moves addresses they drop out of the CPS. Job-changers - particularly those that get large wage increases - are more likely to move locations than job-stayers. So, the CPS data may be downward biased for the wage growth of job-changers because the data does not capture the large wage changes of job-changers who move. None-the-less, the patterns in the Atlanta Fed data are broadly similar to what we show in the main paper using ADP data. In particular, as seen in Appendix Figure B.5, the gap in wage growth between job-changers and job-stayers doubled during the inflation period–just like the doubling observed in the ADP data. However, relative to the ADP data, the wage growth of job-changers relative to job-stayers is smaller in levels both during the pre-period and the inflation period consistent with the fact that the CPS may be missing some of the big wage changes of job-changers who also change residences.[42]

B.7. Corporate Profits

Appendix Figure B.6 shows the corporate profit to GDP ratio in the United States between 2016 and 2024 (quarterly). We downloaded this data directly from the FRED website. In particular, we used the series Corporate Profits After Tax (without IVA and CCA Adjustments)

[42]There are other differences between the ADP data and the CPS data in terms of the wage change measures of job-stayers vs job-changers. For example, the ADP Wage Tracker Index also includes signing bonuses and other forms of income in their wage series for job-stayers and job-changers.

Figure B.5: Nominal Wage Changes of Job-Stayers vs Job-Changers: Atlanta Fed Wage Tracker

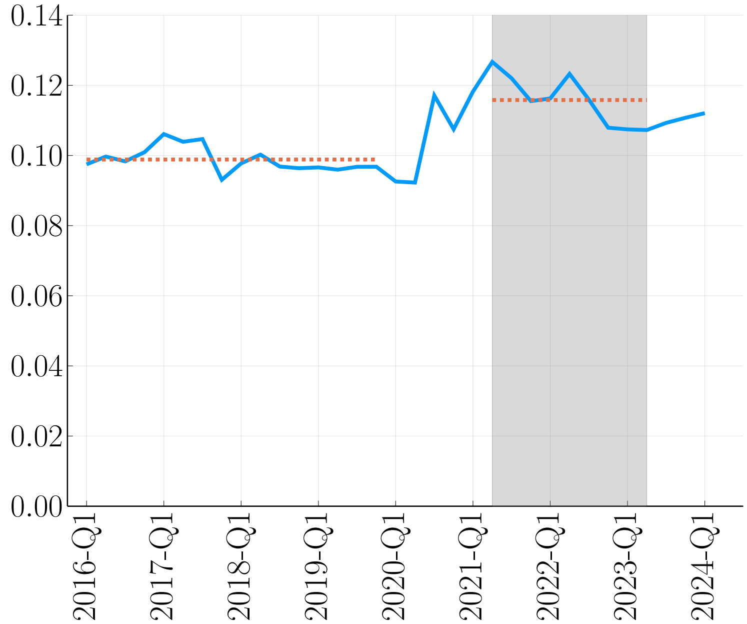


Notes: Figure shows nominal wage growth of job-stayers (red bottom line) and job-changers (grey top line) from the Atlanta Fed's Wage Tracker Index. See text for additional details of the data. We downloaded this figure directly from the Atlanat Fed's Wage Tracker website.

and divided that series by US Nominal GDP. As seen from the figure, the corporate profit to GDP ratio jumped from about 10% in the 2016-2019 period to 11.6% during the inflation period. The corporate profit to GDP ratio during the inflation period is the highest it has been since 1950. Between 1950 and 2020, there were only 9 quarters where the corporate profit to GDP ratio exceeded 11% and there were no quarters where the ratio exceeded 12%. The current corporate profit to GDP ratio is at historically high levels. It should be noted that the corporate profit to GDP ratio was also at historically high levels in 1950, 1974, and 1979 – all periods where the both the inflation rate was high and the labor market was not particularly strong. Specifically, between 1950 and 2000, there were only four periods when the corporate profit to GDP ratio exceeded 7%; three of those were the early 1950s, 1974, and 1979.

The rise in the corporate profit to GDP ratio is consistent with the prediction of our model where firm labor market power increased during the inflationary period because nominal wages are sticky. The rise in the corporate profit to GDP ratio at face value is inconsistent with other theories suggesting firm labor market power decreased during the post-pandemic period due to the labor market being tight.

Figure B.6: Corporate Profits to GDP Ratio



Notes: Figure shows the U.S. corporate profits (after tax, without inventory valuation adjustment and capital consumption adjustment) relative to nominal GDP. Data from the U.S. Bureau of Economic Analysis retrieved from FRED, Federal Reserve Bank of St. Louis.

C Alternate Mechanism Analysis

In this section, we discuss the procedure for exploring other shocks that can generate a rising vacancy-to-unemployment rate through the lens of our model. In particular, we define the size of the various other shocks we explore so they roughly match our baseline increase in the vacancy-to-unemployment rate on impact from the one-time 13.5% increase in inflation (shown in Panel A of Figure 15); one impact of our baseline one-time inflation shock, the vacancy-to-unemployment rate increased by 8.5%. Specifically, we explore four different shocks: a positive shock to aggregate productivity (A_t), a negative shock to the household discount rate (ρ), a negative shock to the level of the vacancy posting cost (K), and a negative shock to the value of non-employment (B). We calibrate the model so all four of these shocks increase vacancies relative to unemployment at roughly the same magnitudes observed in our baseline model of the one-time inflation increase. Throughout these additional exercises, we still impose nominal wage rigidities.

Appendix Table C.1 shows the results of these exercises. Across the columns are the different shocks. In the first column is our baseline shock of a one-time monetary expansion such that it increases the price level by 13.5% on impact. These baseline results are described in the first set of counterfactuals in Section 5. In columns 2-5, respectively, we show the results for the one-time unexpected productivity increase (A_t), lower discount rate (ρ), lower vacancy posting cost (K) and lower non-employment benefit (B). The rows highlight various labor market outcomes. The first four rows measure how various labor market flows respond upon: the vacancy to unemployment rate (row 1), the percentage change in E-E flows (row 2), the percentage change in U-E flows (row 3) and the percentage change in the layoff rate (row 4). All five shocks – by design – match the increase in the vacancy-to-unemployment rate; the shock sizes were chosen to match the roughly 8.5 percentage point increase in the vacancy to unemployment rate. Key features of the data during the recent inflation period were that the E-E rate increased sharply, the U-E rate hardly changed, and the layoff rate fell. In order to match the rising vacancy-to-unemployment rate, all of the other generate a relatively large increase in the U-E rate and very small increases in the E-E rate. Normal hot labor market shocks that causes measured market tightness to increase do so by making the returns to working increase relative to the returns to staying at home implying a larger increase in the U-E rate. Notice, only the large productivity shock results in a large decline in layoffs. In our baseline model, the large inflation reduces workers' real wages relative to their productivity; this makes workers relatively cheap from the firm's perspective reducing their desire to layoff workers. With the productivity shock and sticky wages, the story is similar. The positive productivity shock reduces worker real wages relative to their productivity making them cheap from the firm's perspective.

Rows 5-7 show the log change in real wages after 12 months, the change in per-period real wage growth on impact for job stayers, and the change in per-period real wage growth for job changers. In the data, during the inflation period real wages fell and the gap in the growth rate of job-changers grew sharply relative to job-stayers. Only our baseline shock can generate a large decline in real wages while simultaneously generating an increase in the vacancy-to-unemployment rate. The productivity shock increases real wages one year out. The other three shocks have little effect on real wages. Importantly, only the inflation shock in column 1 can generate a sharp increase in the real wage growth of job-stayers relative to job-changers. In steady state, the real wage growth of job-changers is about 5 percentage points higher than job-stayers. For the other shocks, this 5 percentage point gap remained. It is only with the baseline shock that the gap in wage growth between job-stayers and job-changers widened.[43] As the table shows, the only shock that matches the rising in the vacancy-to-unemployment rate will simultaneously matching other labor market outcomes is our baseline shock.

[43]The last row shows percentage point change in the unemployment rate after one-year. This change is similar across all the shocks.

Table C.1: Comparison of alternative mechanisms

Variable	Baseline	Higher Agg. TFP	Lower ρ	Lower K	Lower B
Δ V/U Ratio	8.4	8.4	8.7	8.7	8.4
% Δ EE Rate	41.3	7.5	2.9	5.3	2.6
% Δ UE Rate	0.3	2.9	5.5	4.2	5.3
% Δ Layoff Rate	-100.0	-70.7	-4.6	44.7	-3.1
% Δ Avg. Log Real Wage	-2.3	1.4	-0.5	0.2	-0.5
Avg. Log Real Wage Growth (Stayers)	8.2	5.3	4.8	5.0	4.8
Avg. Log Real Wage Growth (Switchers)	18.9	11.9	10.4	10.5	10.4
Δ Unempl. Rate	-0.3	-0.2	-0.4	-0.1	-0.4

Notes: This table compares the effects of different shocks on the labor market. See text for additional details.