A Theory of How Workers Keep Up With Inflation[*]

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January 2026

Abstract

We develop a model that integrates modern theories of labor market flows with nominal wage rigidities to study the consequences of inflation on the labor market. Nominal wage stickiness incentivizes workers to engage in job-to-job transitions after an unexpected increase in the price level. Such dynamics lead to a rise in aggregate vacancies associating a seemingly *tight* labor market with *lower* real wages—two facts observed during the recent inflation period. The calibrated model jointly matches aggregate and cross-sectional trends in worker flows and wages during the 2021-2024 period. Using historical data, we show that prior periods of high inflation were also associated with increasing vacancies and upward shifts in the Beveridge curve. Our results suggest that policymakers and academics should be cautious about viewing the rise in the vacancy-to-unemployment rate as a sign of a tight labor market during inflationary periods without holistically looking at other labor market indicators.

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

[*]We thank Yash Singh and Giyoung Kwon for outstanding research assistance and Gabe Chodorow-Reich, Joe Hazell, Larry Katz, Guido Lorenzoni, Ben Moll, Simon Mongey, Giuseppe Moscarini, Benjamin Schoefer and five anonymous referees for providing us with extremely helpful comments. We also thank seminar participants at UC Berkeley, Chicago, Columbia, Duke, Harvard, LSE, MIT, Michigan, NYU, Ohio State, Oxford, Rochester, Stanford, UCLA, UT-Austin, Yale, the ECB, the Federal Reserve Board, the Central Bank of Canada, and the Federal Reserve Banks of Atlanta, Boston, Minneapolis, and St. Louis as well as participants at a variety of other conferences. 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.

1 Introduction

Decades of low and stable inflation in the U.S. ended with the inflation spike of 2021. Whereas inflation had hovered annually at around 2.2 percent between 2000 and 2019, prices rose by over 14 percent cumulatively between April 2021 and May 2023. The unemployment rate continued to decline through the fall of 2021, stabilizing at pre-pandemic levels for the remainder of this period. At the same time, vacancy postings shot up and labor market tightness, measured by the aggregate vacancy-to-unemployment (V/U) ratio, reached historically high levels by mid-2022, as shown in Panel A of Figure 1.1. High inflation, low unemployment, and a high V/U ratio all pointed towards an economy that was "running hot" with too many firms chasing after too few workers, a narrative that was articulated by both policymakers and academics. In his post-FOMC press conference on November 2, 2022, Chair Powell declared that "the broader picture is of an overheated labor market where demand substantially exceeds supply."

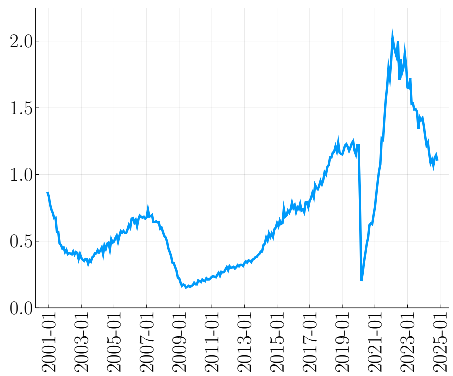
But was the labor market "overheated" during this period? Not according to real wages, which fell sharply with the rise in inflation. As seen in Panel B of Figure 1.1, real wages for the median worker, as measured by the Atlanta Fed's Wage Tracker Index, remained persistently below their 2019 levels from the start of the inflationary period through mid 2024. As of December 2024, real wages for the median worker were still 3.8% below where they were predicted to be based on pre-2020 trends. Consistent with declining real wages, survey evidence documented that workers unambiguously perceived their well-being to have declined during the recent inflation period.[1] The juxtaposition of the seemingly "hot labor market" implied by the rising V/U ratio with the persistent decline in real wages questions the role of a tight labor market in driving up prices during the recent period.

With the above facts as a backdrop, our paper makes five contributions to the literature. First, we develop a new framework that combines modern models of labor market flows with nominal wage rigidities. While the model has many potential applications, we show that it can be used to explore the aggregate and distributional consequences of "inflation shocks" on labor market outcomes and worker well-being.[2] We show theoretically that unexpectedly high inflation induces workers to search more on-the-job, providing an incentive for firms to post

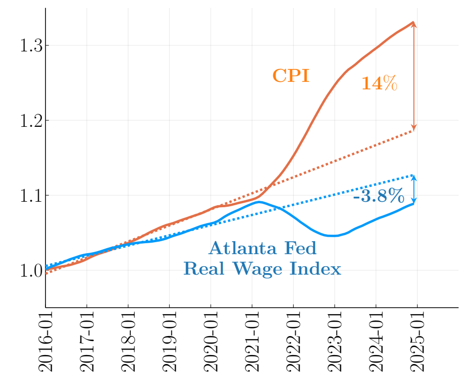
[1] See Stantcheva (2024) and Afrouzi et al. (2024). The findings in these papers are consistent with the reported decline in measures of life satisfaction among respondents in Gallup surveys during the 2021-2025 period. See, for example, `https://news.gallup.com/poll/655493/new-low-satisfied-personal-life.aspx`.

[2] In the model, the "inflation shock" will be an unexpected exogenous increase in the price level. The goal of the paper is not to explain the causes of the recent inflation but, instead, to assess how inflation itself can causally affect labor market dynamics.

Figure 1.1: Vacancy-to-Unemployment Ratio, CPI and Real Wages Over Time



Panel A: Vacancy-to-Unemployment Ratio: 2000-2024



Panel B: CPI and Real Wages: 2016-2024

Notes: Panel A shows the vacancy-to-unemployment rate from 2001M1 through 2024M12, where vacancies come from the JOLTS survey. Panel B shows the evolution of the CPI (red line) and the Atlanta Fed's Nominal Wage Index deflated by the CPI (blue line). The dashed lines in the figure project the growth rate in each series from January 2016 and December 2019 over the entire sample period. See Section 2 for additional details on the series construction.

more vacancies during periods of declining real wages. Second, we show quantitatively that our model, calibrated using pre-2020 data, matches well the time series and cross-sectional trends in U.S. labor market flows and wages during the 2021-2024 period, with the only underlying labor market shock being the observed inflation dynamics. Third, we use historical data from 1950 to 2019 to show that vacancies have systematically increased and the Beveridge curve has systematically shifted upward during periods of prior inflation. These findings highlight that the implications of our model are not simply limited to the recent post-pandemic inflation. Fourth, we use the model to show that the recent inflation substantially reduced worker welfare throughout the income distribution, providing a model-driven reason why workers report disliking periods of unexpectedly high inflation (Shiller, 1997; Stantcheva, 2024). Finally, our model yields novel additional real costs and benefits of inflation to an economy stemming from costly job search, costly wage renegotiation, and declining firm layoffs.

We begin the paper by using data from the *Job Openings and Labor Turnover Survey* (JOLTS), the *Current Population Survey* (CPS), the *Atlanta Fed Wage Tracker Index*, and *ADP's Pay Insights* to document a series of facts about labor market flows and wages during the 2021-2023 inflation period. We show that, relative to the 2016-2019 period, E-E flows, quits, and vacancies jumped during the recent inflation period, while the layoff rate fell and the U-E rate remained relatively stable. These patterns were pronounced across all industries. Likewise, relative to the pre-period, nominal wage growth grew significantly more for job-changers than for job-stayers. Real wages declined more for higher wage workers than for lower wage workers during the inflation period. The collective wage patterns, including those shown in Figure 1.1, persist even when we consider occupations that are not amenable to working from home.

Motivated by these patterns, we develop a framework that combines a modern macro-labor search model with sticky wages, consistent with the observed micro-data on nominal wage adjustments and rich worker heterogeneity. Workers decide whether to renegotiate their wage, quit to unemployment, or search for a new job, while firms determine whether to lay workers off.[3] Nominal wages are sticky within a match. Our model postulates two main channels for employed workers to overcome the stickiness of their nominal wages. First, workers can pay a randomly drawn fixed cost to renegotiate their wages to any level at any time. Second, we assume that the wages of new hires are flexible, meaning that workers can also adjust their nominal wages by searching on the job and potentially moving to a match with a new employer. Job search is frictional and directed on the part of both workers and firms.

To examine how different workers are affected by an unexpected temporary burst of inflation, the model includes heterogeneous worker types who differ in their latent productivity. In addition to ex-ante heterogeneity, the productivity of the employed (unemployed) is a Brownian motion process with positive (negative) drift. We also allow the worker's flow benefits of non-employment and the cost of vacancy posting on the part of firms to flexibly scale with worker productivity. These forces allow for a potential mechanism by which the labor market decisions of high and low wage workers can differ in response to the same underlying labor market shocks.

On the methodological front, the model requires solving for the equilibrium strategies of the game between matched workers and firms. Due to nominal wage rigidities, we cannot rely on the usual equivalence to a planner's problem that maximizes the surplus of the match on behalf of firms and workers. Instead, we use a Markov Perfect Equilibrium concept in continuous time to characterize both firms' and workers' decisions. Workers' strategies consist of which submarket to enter while unemployed, and once within a match, when

[3] Our framework shares similarities to the model of inefficient separations with nominal wage rigidities found in Blanco, Drenik, et al. (2024). Such endogenous quits, layoffs, and wage renegotiations with sticky wages introduce the key ideas of models of inaction from the output pricing literature (e.g., Barro, 1972; Sheshinski and Weiss, 1977) into a modern macro labor model with search.

to renegotiate, when to quit, or when to search for a new job. Different submarkets offer different combinations of offered wages and job-finding rates. Firms' strategies involve determining when to lay off their employed workers. Our contribution here is to recast the strategic interaction between matched firms and workers as a stochastic non-zero-sum game with stopping times in continuous time. This approach characterizes the equilibrium conditions as two Hamilton-Jacobi-Bellman Variational Inequalities (HJBVIs) describing optimal policies and value functions, and allows us to use efficient numerical methods to solve for the equilibrium.

Through the lens of the model, an increase in inflation reduces the real wages of matched workers. These workers respond by increasing their on-the-job search effort, resulting in an inflation-induced increase in both aggregate quits and E-E flows. The spike in workers' on-the-job search increases the incentive for firms to post vacancies, thereby resulting in an inflation-induced spike in aggregate vacancies. Additionally, workers adjust their on-the-job search toward submarkets with higher job-finding rates, lower starting wages, and lower job-filling rates. This composition shift generates an increase in aggregate vacancy duration. The model also allows for workers to forgo search and instead choose to engage in costly renegotiation with their firm to increase their real wage. Finally, the reduction in workers'real wages systematically moves them further away from the firm's layoff threshold, resulting in an inflation-induced reduction in aggregate layoffs.

We then use a variety of micro-data sources in the years prior to 2020 to calibrate the key labor market parameters of our model. In particular, we use administrative payroll data on the frequency of wage changes and the distribution of the size of wage changes to calibrate the parameters governing nominal wage rigidities. We also use both time series and cross-sectional data on worker flows to help discipline the parameters governing the search environment. For example, we discipline the extent to which the value of non-employment and vacancy posting scales with productivity with micro data on differences in job-finding rates and job-to-job flows across the wage distribution during the pre-inflation period. We estimate that the value of non-employment is relatively higher and the cost of posting a vacancy is relatively lower for low-productivity workers, implying they are more responsive to unexpected increases in the price level.

Using the calibrated model, we find that an unexpected temporary inflation shock of a size comparable to the inflation experienced in the U.S. during the 2021-2023 period quantitatively matches key patterns observed in the labor market at that time. In particular, our quantitative model matches both the decline in real wages and the increase in the aggregate vacancy-to-unemployment rate shown in Figure 1.1. Additionally, the model matches the fact that quits and E-E flows increased, layoffs declined, real wages fell more for higher wage workers, and real wages fell more for job-stayers relative to job-changers. Finally, we show that the model generates an inflation-induced upward shift in the Beveridge curve, similar to what was observed in the U.S. economy during the last few years due to the increased vacancies created in response to the higher E-E churn.

We next turn to measuring the effect of recent inflation on worker welfare. We find that inflation reduced the average welfare of workers in all deciles of the income distribution. In our preferred counterfactual, we estimate that the median worker lost about 20% of one month's income – or about $1,000 – from the recent inflation period. We estimate that the majority of the welfare losses stem from the nominal wage rigidities, which transferred resources from workers to firms; this finding is consistent with the historically high corporate profit rates experienced by US firms during the 2021-2023 period. We also show that the increased search and renegotiation costs incurred by workers to have their real wages keep up with inflation further reduced worker welfare beyond the real wage declines. These findings highlight additional real costs of inflation through costly actions taken by workers in response to inflation. Conversely, we also find that workers received offsetting welfare gains from the recent inflation stemming from reduced layoffs.

Looking beyond the inflation surge of 2021, in the last section of the paper, we use historical data to show that periods of high inflation are systematically associated with increasing vacancy-to-unemployment rates and upward shifts in the Beveridge curve. Using Barnichon (2010)'s unified vacancy series, we identify eight periods during which the vacancy-to-unemployment rate substantially exceeded its long-run average. Four of those periods were associated with very high inflation: those periods were in the early 1950s, the mid-1970s, the late 1970s, and the current post-COVID period. All of these periods were marked by large negative aggregate supply shocks that contributed in part to the high inflation. The other periods of high vacancy-to-unemployment rates had relatively low inflation and a sharply declining unemployment rate consistent with moving along a stable Beveridge curve. We then document that the vacancy rate and the vacancy-to-unemployment rate both systematically increased when inflation was high during the 1950-2019 period conditional on the aggregate unemployment rate. These results provide additional empirical support for our theory using data prior to the post-pandemic period. Collectively, our findings suggest that academics and policymakers should be cautious about viewing the rise in the V/U ratio as a sign of an overheating labor market during inflationary periods without holistically looking at other labor market indicators.[4]

Related Literature. A key implication of our model is that accounting for the role of vacancies targeted toward employed vs. unemployed workers is key for understanding the recent rise in the aggregate V/U ratio and the shift in the Beveridge curve. To that end, our paper provides additional supporting evidence for the mechanism highlighted in Cheremukhin and Restrepo-Echavarria (2023) which argues that the shape of the Beveridge curve depends on the extent to which outstanding vacancies are filled with E-E transitions as opposed to U-E transitions. Likewise, our paper is related to Moscarini and Postel-Vinay (2023) which introduces on-the-job search into a monetary DSGE New-Keynesian model and shows that the ratio of E-E transitions to U-E transitions serves as a key predictor of inflationary pressures. Complementing this literature, our paper demonstrates that inflation itself can alter the pattern of job-to-job transitions and vacancy creation, leading to shifts in the Beveridge curve. Together, these mechanisms highlight the importance of distinguishing between job-to-job transitions and transitions from unemployment when analyzing inflationary episodes.

A key element of our framework is that wages are more flexible for job-changers compared to job-stayers during inflationary periods. Recently, Hazell and Taska (2024) highlights an asymmetry between the relative upward and downward cyclicality of new hire wages. Using job-posting data to look at within job variation, Hazell and Taska (2024) find that nominal wages do not fall for a given job when economic conditions contract similar to the results for job-stayers.[5] However, nominal wages of job-changers rise sharply during periods of economic expansions. The estimated nominal wage growth of job-changers during periods of economic expansions documented in Hazell and Taska (2024) is much larger than the nominal wage growth of job-stayers shown in Grigsby, Hurst, and Yildirmaz (2021) during similar years. The findings in Hazell and Taska (2024) motivate our assumption of the relative flexibility of job-changer wages during inflationary periods. Moreover, their conclusions are also consistent with the empirical finding from the ADP payroll data that shows the gap between the nominal

[4] Recently, both Benigno and Eggertsson (2023) and Autor, Dube, and McGrew (2024) have interpreted the rising V/U ratio as a sign that the U.S. labor market was tight during the post-pandemic period.

[5] Gertler, Huckfeldt, and Trigari (2020) and Grigsby, Hurst, and Yildirmaz (2021) examine the relative cyclicality of new hire wages without examining an asymmetry between periods when wages should be rising or when they should be falling. Most of the identification in these papers come from periods when the unemployment rate rises sharply as it did during the Great Recession. As seen from Hazell and Taska (2024), both the wages of incumbent workers and new hires are downwardly rigid during economic contractions.

wage growth of job-changers increased sharply relative to job-stayers during the 2021-2023 inflation surge.

Our work is also related to a set of recent papers showing how worker well-being is affected by recent inflation. Hajdini et al. (2022), Pilossoph and Ryngaert (2024), and Pilossoph, Ryngaert, and Wedewer (2024) all highlight how increased inflation can result in workers searching more for another job. Pilossoph and Ryngaert (2024) use survey data to show that workers with higher inflation expectations increase their job search effort. They then develop a decision-theoretic model of job search with nominal wage rigidities to show that surprise inflation can increase workers' on-the-job search effort and lower the reservation wage for job transitions. Separately, Pilossoph, Ryngaert, and Wedewer (2024) further formalizes these insights by extending the model of Postel–Vinay and Robin (2002) to include endogenous search effort and a price level with deterministic trend inflation. Using this extended framework, they show that unexpected inflation can also have allocative consequences by inducing workers to move to better matches. However, they show that these allocative effects were quantitatively small during the recent inflation period.

Guerreiro et al. (2024) fielded a novel survey in early 2024 asking respondents whether they took costly actions—asking their boss for a raise, partaking in union activity, or soliciting external job offers—in response to the recent inflation. They find that about one-fifth of all workers engaged in costly actions to raise their wages during the recent inflation period. They then developed a menu cost model of nominal wage adjustments to show how workers optimally choose to take more of these costly actions during inflationary periods given nominal wage rigidities. Calibrating the model with their novel survey, they find that incorporating the costly actions that workers took to have their real wages keep up with inflation doubled the aggregate cost of inflation to workers, relative to the costs implied by falling real wages alone.

Finally, there is an emerging literature documenting the shift towards working-from-home (WFH) during the post-pandemic period, particularly for higher wage workers.[6] This literature has shown that workers value the ability to work from home (Cullen, Pakzad-Hurson, and Perez-Truglia, 2025), that such an amenity can reduce worker turnover (Bloom, Han, and Liang, 2024), and WFH can reduce worker productivity in some sectors (Emanuel, Harrington, and Pallais, 2023). Closest in spirit to our paper, Bagga et al. (2025) quantify a structural model of the labor market to assess the importance of shifting job amenities (such as WFH)

[6]See, for example, Dingel and Neiman (2020), Bick, Blandin, and Mertens (2023) and Hansen et al. (2023).

on worker flows and wages during the post-pandemic period. They show that the sudden availability of WFH can also generate declining real wages and increasing worker churn. As we highlight throughout, both our story and the WFH story have empirical support in the data and emerge as two of the leading explanations for post-pandemic labor market dynamics.

2 The U.S. Labor Market During the Recent Inflation Period

We refer to the recent "*inflation period*" in the United States as beginning in April 2021 and extending through May 2023; for each month during this period, the year-over-year CPI inflation rate exceeded 4%. The cumulative price level increase was roughly 13.5% during this 26-month period. For comparison, the inflation rate in the United States averaged about 2% per year during the 2000-2019 period and averaged just over 3% at an annualized rate during the "*post-inflation*" period of May 2023 through December 2024.

In this section, we document a set of facts about how labor market flows and wages evolved during the recent inflation period within the United States both in the aggregate and across different income groups. We compare the labor market outcomes in the "*inflation period*" to a *"pre-period"* defined as the pre-pandemic period spanning January 2016 through December 2019. Collectively, these patterns motivate the setup of our model described in the next section. In later sections, we evaluate the success of our model by its ability to match the broad time series patterns documented below.[7]

2.1. Aggregate Wages and Employment During the Inflation Period

Figure 1.1 above shows the decline in real wages experienced by the median U.S. worker during the inflation period. To measure trends in real wage growth, we use data from the *Atlanta Federal Reserve's Wage Tracker Index*. The *Atlanta Fed Wage Tracker Index* uses the panel component of the *Current Population Survey (CPS)* to measure the composition-adjusted year-over-year change in workers' per hour nominal wages on their main jobs. Given the Atlanta Fed provides a monthly series on year-over-year wage growth, we create a series of monthly real wage growth by deflating by the CPI inflation rate over the corresponding period. We normalize our real wage index to 1 in December 2015.

Additionally, as seen in Appendix Figure B.2, the average employment-to-population ratio for those aged 15-65 and the average U.S. unemployment rate remained roughly constant between the pre-period and the inflation period. While the employment rate fell and the

[7] A more detailed discussion of all data used in this section can be found in the Online Appendix.

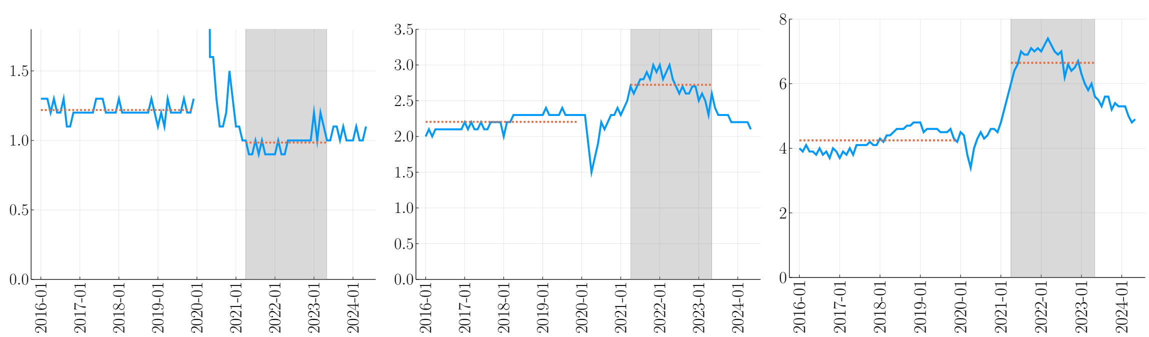
unemployment rate increased sharply during the pandemic, both returned to roughly pre-pandemic levels by the fall of 2021. These patterns also occurred within various demographic groups. Given this, the results we show below are unchanged whether or not we control for composition shifts between the pre-period and the inflation period; neither the level nor the composition of the labor force changed much between *pre-pandemic* and *inflation* periods.

2.2. Aggregate Quits, Layoffs, and Vacancies During the Inflation Period

Figure 2.1 shows the trends in the monthly layoff rate, quit rate, and vacancy rate for the United States between 2016 and 2024, using data from the BLS's *Job Openings and Labor Turnover Survey* (JOLTS). The JOLTS dataset provides a snapshot of worker hiring and separation flows for a nationally representative sample of non-farm businesses and government employers during a given month.

Layoff Rate. Panel A of Figure 2.1 shows the time series trend in the layoff rate prior to, during, and after the inflation period. Between January 2016 and December 2019 (the "*pre-period*"), the average layoff rate was fairly constant at about 1.22% per month. However, throughout the inflation period, the monthly layoff rate fell sharply to about 0.98% per month; during this period, the layoff rate was at its lowest level since the JOLTS data started in 2000. Relative to the pre-period, firms terminated workers at a much lower rate during the inflation period.

Figure 2.1: Layoff Rate, Quit Rate, and Job Opening Rate 2016-2024, JOLTS Data



Panel A: Layoff Rate | Panel B: Quit Rate | Panel C: Vacancy Rate

Notes: The figure shows the monthly layoff, quit, and vacancy rates for the U.S. economy between 2016 and 2024 using the BLS's JOLTS data. The dashed red lines show the average of the series during the 2016-2019 pre-period and then separately during the inflation period (shaded area), respectively. To make the graph easier to read, we excluded the historic spike in the layoff rate during the beginning of the COVID recession from the figure.

Quit Rate. Panel B of Figure 2.1 shows the time series trend in the quit rate during the 2016-2024 period. From 2016 through 2019, the quit rate averaged about 2.2% per month. During the inflation period, the quit rate jumped to an average of about 2.7% per month. The time series path of the quit rate closely followed the time series path of inflation; for example, both the inflation rate and the quit rate peaked in the second quarter of 2022. By early 2024, both the quit rate and the inflation rate had returned to their 2016-2019 levels.

Vacancy Rate. Panel C of Figure 2.1 shows the time series patterns of the vacancy rate. The average monthly vacancy rate jumped from 4.25% per month during the 2016-2019 period to 6.65% per month during the inflation period. Again, the time path of the vacancy rate tracked closely the time path of inflation during the 2021 to 2024 period.

2.3. Worker Flows During the Inflation Period

The quit rate from the JOLTS data shown above 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). In this subsection, we use data from the *Current Population Survey* (CPS) to further highlight that the increase in quits from the JOLTS data was primarily driven by an increase in job-to-job flows and not driven by an increase of workers into non-employment.[8]

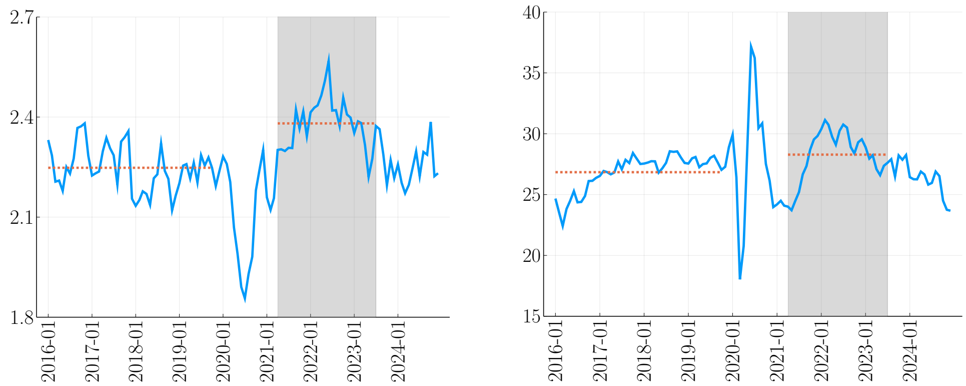
Panel A of Figure 2.2 shows the time series of a three-month moving average of the monthly E-E rate for U.S. workers during the 2016-2024 period.[9] In the 2016-2019 period, the average E-E rate was 2.24% per month. During the 26-month inflation period, the E-E rate jumped to an average of 2.38% per month (p-value of difference < 0.01). In mid-2022, the E-E rate peaked at 2.57% per month. The CPS data complement the JOLTS data by showing that the increasing quit rate is accompanied by an increase in employer-to-employer transitions.

Panel B of Figure 2.2 shows the time series patterns for monthly U-E flows during 2014-2024. The monthly job-finding rate measures the share of unemployed workers who transition to employment during a given month. There was no statistically significant change in the U-E

[8] Ellieroth and Michaud (2024) document that quits to non-employment did not increase during the 2021-2023 period relative to the 2016-2019 pre-period. Appendix Figure B.3 uses data from the CPS to also show that there was relatively little increase in the flow of non-participant workers into employment during the 2021-2024 period.

[9] For this analysis, we use the measure of E-E flows created in Fujita, Moscarini, and Postel-Vinay (2024) based on CPS data. The data can be downloaded directly from the Philadelphia Federal Reserve's website `https://www.philadelphiafed.org/surveys-and-data/macroeconomic-data/employer-to-employer-transition-probability`.

Figure 2.2: E-E and U-E Flows 2016-2024, CPS Data



Panel A: E-E Rate   Panel B: U-E Rate

Notes: Panel A of Figure shows the time series pattern of monthly E-E flows using the series created by Fujita, Moscarini, and Postel-Vinay (2024). Panel B shows the time series pattern of monthly U-E flows downloaded directly from the FRED database. The dashed red lines in both panels provide the average flows during the pre-period and the inflation period (shaded area), respectively. For both series we plot a three month moving average.

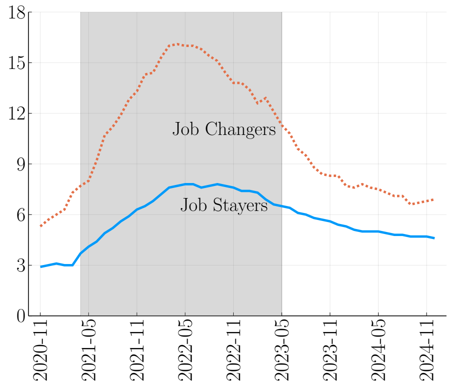
rate between the pre-period and the inflation period. Unemployed workers found employment in a given month at roughly the same 27% rate during both the inflation period and the pre-period. While it is normally the case that changes in the U-E rate explain the vast majority of unemployment dynamics (Shimer, 2012), we show in Online Appendix Figure B.4 that changes in the job-finding rate explained relatively little of the unemployment dynamics during the 2021-2024 period.[10]

2.4. Wage Growth, Job-Changers vs Job-Stayers

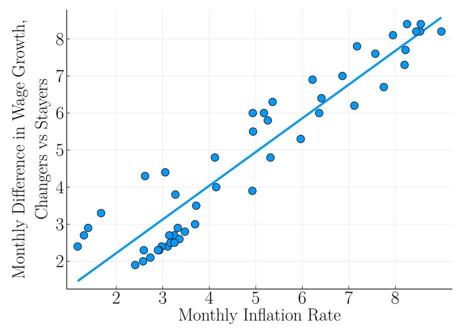
We next use data from *ADP Pay Insights* to examine the relative earnings growth of job-changers vs. job stayers during the inflation period. ADP is a payroll processing company that processes payroll for roughly one-fifth of the U.S. labor market. Given the size of their data, ADP can track earnings for workers who remain with the same firm and for workers who transition from one firm to another. Our analysis with the ADP data spans the 2020 to 2024 period, given that ADP Pay Insights only started publishing earnings growth data for broad groups such as job-changers vs. job-stayers starting in 2020. It should be noted that the ADP data reports the nominal growth in worker annual earnings as opposed to hourly wages.

[10]We show the decomposition of changes in the unemployment rate to changes in the U-E rate and changes in the layoff margin. We thank Joe Hazell for suggesting we add this decomposition to our appendix.

Figure 2.3: Nominal Wage Growth 2020-2024, Job-Changers, and Job-Stayers



Panel A: ADP Wage Growth, By Switching Status



Panel B: Changer-Stayer Difference vs. Inflation Rate

Notes: Panel A of the figure shows the median nominal income growth of job-stayers (solid line) and job-changers (dashed line) during the October 2020 through December 2024 period from the ADP Pay Insights database. Panel B plots the monthly difference between the two series vs the monthly year-over-year inflation rate.

Panel A of Figure 2.3 shows the median annualized nominal earnings growth (year-over-year) for (i) workers who remained with their same employer during the prior 12 months (job-stayers, solid line) and (ii) workers who switched employers during the prior 12 months (job-changers, dashed line). During the middle of the inflation period, the median nominal earnings growth of job-changers increased by about 8 percentage points relative to early 2021 (from about 8% to 16%). By the middle of the inflation period, the median annualized nominal earnings growth of job-stayers increased by only about 4 percentage points (from about 3% to 7%). Panel B of the figure shows that the gap in wage growth between job-changers and job-stayers is strongly correlated with the monthly inflation rate. As seen from the panel, job-changers were able to get even larger wage increases relative to job-stayers when inflation was higher. By 2024, the relative gap in nominal wage growth between job-changers and job-stayers returned to early 2021 levels. Given that the ADP Pay Insights data started in late 2020, there is no direct way to compare the gap in nominal earnings growth between stayers and changers to a pre-period. However, Grigsby, Hurst, and Yildirmaz (2021) find that the median nominal base wage growth gap between job-changers and job-stayers in the ADP sample was roughly 4 percentage points during the 2008-2016 period that they analyzed. Given that, the gap in 2024 appears to have returned to roughly pre-pandemic levels.

2.5. Heterogeneity in Labor Market Outcomes Across Occupations, Worker Types, and Sectors

In this subsection, we briefly summarize how the worker flows and wage dynamics documented above vary across occupations, worker types, and sectors. We provide a more extensive discussion in the Online Appendix.

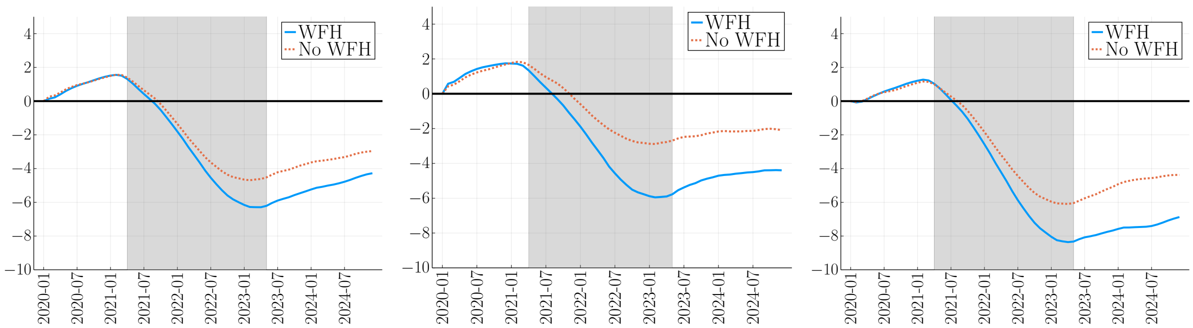
Real Wage Declines Occurred in Occupations Not Amenable to Working From Home. As noted in the introduction, there was a large shift in the share of individuals working from home after the COVID-19 pandemic, with the increase being largest for higher wage workers. The ability to work from home (WFH) is an amenity that some workers value, which could have put downward pressure on real wages during the 2022-2024 period. Figure 2.4 plots real wages over time by potential WFH status to assess how much of the decline in real wages observed during the post-pandemic period could potentially be attributed to the shift to work-from-home. Specifically, Figure 2.4 documents the evolution of real wages separately for workers in occupations amenable to WFH (solid line) and for workers in occupations not amenable to WFH (dashed line) based on the Dingel and Neiman (2020) classification.[11] To facilitate comparison across the various real wage series, Figure 2.4 plots real wages *relative* to their occupation-by-group predicted trend, where, as in Figure 1.1, the trend is based on 2016-2019 data.

Panel A of the figure shows the patterns of median real wage growth for all workers in the U.S. economy, broken down by WFH status. Roughly half of all individuals work in occupations that were classified as being amenable to WFH by the Dingel and Neiman (2020) measure. Consistent with WFH being an amenity valued by workers, real wages fell more in WFH occupations relative to the trend, as compared to non-WFH occupations during the post-pandemic period. However, consistent with the hypothesis of our paper, real wages still fell sharply in non-WFH occupations. In particular, towards the end of the inflation period in early 2023, real wages were roughly 5% below trend in non-WFH occupations. As of December 2024, real wages were still roughly 3% below trend in non-WFH occupations. As a result, the ability to WFH may have had an effect on depressing real wages during the post-pandemic period (the difference between the solid and dashed lines), but it was not the

[11] We use the underlying processed CPS data produced by the Atlanta Fed for their Wage Tracker Index for this analysis. We thank Melinda Pitts from the Atlanta Fed for providing us with their processed microdata. Based on occupational task measures, Dingel and Neiman (2020) create a 0/1 indicator for whether workers in over 750 detailed occupations have the ability to work from home. The detailed occupation codes used in Dingel and Neiman (2020) map directly to the CPS occupation codes given their provided crosswalk.

primary reason why real wages fell during the inflation period. The fact that real wages fell sharply, even in occupations not amenable to working from home, reinforces our narrative that the inflation period was one where real wages were depressed despite rising vacancies.

Figure 2.4: % Deviations from trend in Real Wages by Occupation Type



Panel A: All Workers | Panel B: Bottom Quartile | Panel C: Top Quartile

Notes: The figure shows the evolution of real wages *relative to predicted trend* for workers in occupations that are amenable to WFH (solid blue line) and those that are not amenable to WFH (dashed red line), based on the Dingel and Neiman (2020) classification. Panel A shows the patterns for all workers, while Panels B and C show the patterns for workers in the bottom and top quartiles of the aggregate wage distribution. The share of individuals working in WFH occupations in each of the three panels is 47%, 26%, and 67%, respectively.

Real Wage Declines Were Larger for Higher Wage Workers. The Atlanta Fed produces wage series for workers whose wages are in different quartiles of the initial overall wage distribution. Panels B and C of Figure 2.4 show real wages relative to trend for workers in the bottom and top quartiles of the wage distribution by WFH status. Consistent with the patterns documented in Autor, Dube, and McGrew (2024), real wage declines were much larger for workers at the top of the wage distribution relative to those in the bottom. These patterns still hold even after accounting for the differential propensity to WFH across the income groups. For example, in non-WFH occupations, real wages were roughly 6% below trend for top quartile workers and were 3% below trend for bottom quartile workers as of early 2023. As of December 2024, the real wages of top and bottom quartile workers were 4% and 2% below trend, respectively.[12]

[12]Whether the real wages for bottom quartile workers are still below trend as of December 2024 depends on the chosen trend rate. In the appendix, we show results where the trends are defined over the longer 2000-2019 period. We also show patterns for workers in the second and third quartiles, as well as the actual real wage series, as opposed to series relative to trend, for each of the quartiles.

Quits and Vacancies Increased and Real Wages Declined in All Sectors. Online Appendix Table B.3 shows that vacancies and quits increased while real wages fell relative to trend in all broad industry groups during the inflation period. These results suggest that the aggregate patterns highlighted above also hold within broad sectors. Additionally, Figure B.9 shows that 2-digit industries that had the largest increase in quits between the pre-period and the inflation period were also the industries that had the largest increase in vacancies. This finding provides some suggestive evidence for one of the key mechanisms in our paper, that worker churn is related to increasing vacancies.

Subjective Measures of Well-Being Declined During the Inflation Period. In Online Appendix Section B.8, we use various questions from Gallup Analytics to assess how individual measures of subjective well-being evolved during the inflation period relative to the pre-period. Consistent with the patterns of real wages, reported measures of subjective well-being fell sharply during the inflation period for all income groups; however, declines were largest for higher wage workers. These patterns reinforce the survey results in Stantcheva (2024) where workers report strongly disliking inflation because it reduces their purchasing power by eroding their real wages. This set of results suggests that the real wage declines reported above are consistent with self-reported declines in worker well-being.

3 Model

In this section, we develop a model of how workers respond to unexpected changes in the inflation rate and ask whether such changes, all else equal, can causally generate the patterns documented in Section 2.[13]

3.1. Environment

Time is continuous and indexed by t. The economy is populated by a unit measure of workers, denoted by $i \in [0, 1]$. Workers can either be employed ($E_{it} = 1$) or unemployed ($E_{it} = 0$). Workers die at an exogenous rate $\chi > 0$ and are replaced by newly unemployed workers. To focus on and isolate the effects of rigidities in the labor market, we abstract away from rigidities in firm pricing and assume that the price of the homogeneous consumption good is exogenous.

Exogenous Worker Productivity. Worker productivity can be expressed as $Z_{it} = exp(\bar{z}_i + \hat{z}_{it})$ where $\bar{z}_i$ is the worker's permanent productivity drawn at birth from a normal distribution

[13] Our framework builds on and extends the model developed in Blanco, Drenik, et al. (2024).

with mean μ_{z0} and standard deviation σ_{z0}. After birth, a worker's idiosyncratic productivity $\hat{z}_{it}$ evolves according to a Brownian motion with drift such that:

$$\mathrm{d}\log(Z_{it}) = \gamma(E_{it})\mathrm{d}t + \sigma \mathrm{d}W_{it}^{Z}, \tag{1}$$

where the drift $\gamma(E) = \gamma_e$ if $E = 1$ and $\gamma(E) = \gamma_u$ if $E = 0$. We allow the drift to potentially depend on the employment state to account for the potential of on-the-job human capital accumulation while employed and the depreciation of skills while not working. We refer to workers with differing Z's as workers of differing types.

Production Technology. While employed in a match, worker i produces Z_{it} units of output. Such a worker then receives a real wage $W_{it} = \tilde{W}_{it}/P_t$, where $\tilde{W}_{it}$ is the nominal wage and P_t is the exogenous price level with growth rate denoted by π. While unemployed, worker i receives a flow real income of $BZ_{it}^{\phi_b}$, which captures the flow value of non-employment. The parameter ϕ_b measures the extent to which the flow value of non-employment scales with worker productivity. When $\phi_b < 1$, employed low-productivity workers will be, on average, closer to their value of non-employment. ϕ_b will be one important parameter in determining whether the elasticity of worker flows in response to labor market shocks differs across worker types.

Search and Matching Technology. Job search is frictional and directed for both workers and firms. Firms announce wage-specific vacancies to attract workers with productivity Z at a vacancy posting cost of KZ^{ϕ_k}. There is an infinite mass of potential firms that can open a vacancy and hire a worker in any of these markets. Thus, the expected benefit of opening a vacancy in any market must be zero. The parameter ϕ_k measures the extent to which vacancy posting costs scale with worker productivity. When $\phi_k > 1$, it is more expensive for firms to hire a high-productivity worker. ϕ_k will be the second important parameter in determining whether the elasticity of worker flows in response to labor market shocks differs across worker types.

The creation of matches in each market is governed by a standard matching function with constant returns to scale between vacancies and the search intensity of workers. Each worker chooses search intensity s subject to a convex utility cost function that depends on their search effort and employment status, denoted by:

$$S(s; Z, E) = \eta(E)^{1/\phi_s} \frac{s^{1+1/\phi_s}}{1 + 1/\phi_s} Z, \tag{2}$$

where $\eta(E) = \eta_e$ if $E = 1$, $\eta(E) = \eta_u$ if $E = 0$, and $\phi_s > 0$. We assume the disutility of searching on the job is larger than the disutility of searching while unemployed, that is, $\eta_e > \eta_u$. In addition to endogenous separations, matches are also subject to exogenous separation shocks at rate $\delta(Z_{it})$ that possibly varies with worker productivity.

Let $\theta(Z, W)$ denote a measure of tightness in its corresponding market; i.e., the ratio of vacancies to the total effective units of search intensity of workers with productivity Z looking in the market with a real wage W. In a market with tightness θ, workers find jobs with probability $sf(\theta)$ while firms find workers with probability $q(\theta) = f(\theta)/\theta$. As is common in the literature, we assume a Cobb-Douglas matching technology so that the job-finding rate and the job-filling rate are, respectively, $f(\theta) = \theta^{1-\alpha}$ and $q(\theta) = \theta^{-\alpha}$, where $\alpha \in (0, 1)$ is the elasticity of matches to total search intensity. We assume that firms and workers can visit only one market at a time.

Wage Determination within a Match. The key economic mechanism in our model is that nominal wages are sticky for workers within a match. We model the rigidities so that it can potentially replicate the empirical features of the nominal wage change distribution for job-stayers found in the ADP micro data for the 2008-2016 period, as documented by Grigsby, Hurst, and Yildirmaz (2021).[14] The distribution of nominal wage changes has five features. First, there is a large spike at zero, such that about one-third of job-stayers do not receive a nominal wage adjustment during the year. Second, there is another spike in the annual nominal wage change distribution, with about one quarter of job-stayers receiving a nominal wage change in the range of 2-3% per year. Third, there is a missing mass of workers getting small nominal wage adjustments, with only about 5% of job-stayers getting wage changes of about 1%. Fourth, there is a long tail of nominal wage increases above 3% for job-stayers. Finally, there are stark asymmetries in nominal wage changes around zero, with only about 2% of job-stayers receiving a nominal wage cut during a year.

With this empirical distribution in mind, we model worker nominal wage adjustments within a match as follows. First, in a time period $\mathrm{d}t$, with probability $\beta_{\pi^*}\,\mathrm{d}t$, the worker has the opportunity of a "free" wage increase. These free wage increases reset workers' real wages to their Nash-bargained level with the constraint that the nominal wage change must be in the range of 0 and $\Delta\bar{w}_{\pi^*}$. This process proxies for the fact that most employers evaluate their workers' wages once a year and, potentially because of norms, make a decision on whether to give the worker a raise within a range between 0 and some upper bound, such as a 2 or

[14]The online appendix reproduces Figure 2 of Grigsby, Hurst, and Yildirmaz (2021) showing the distribution of year-over-year nominal wage changes for job-stayers.

3% raise. Allowing for free wage changes of this sort helps generate the spikes in nominal wage adjustments at both zero and at 2-3% as observed in the data. Going forward, we set $\Delta\bar{w}_{\pi^*} = 12 \times \pi^*$, where π^* is the monthly steady-state trend inflation in the economy.[15] Allowing for free wage adjustments minimizes the extent to which workers have to expend costly effort to have their wages keep up with unexpected temporary periods of inflation.

Second, we allow workers to pay a random menu cost ψ^+—measured in units of utility and drawn from an exponential distribution—to initiate a wage renegotiation process with their employer to increase their nominal wages to their unconstrained Nash bargained level.[16] This gives workers the opportunity to accelerate their nominal wage adjustment relative to the "free" wage adjustments discussed above. In particular, at any point in time, with probability $\beta_+ \mathrm{d}t$ the worker can pay a stochastic cost $\psi^+ Z$ to initiate a negotiation to increase the current nominal wage. With the remaining probability, renegotiation costs are infinitely large. Finally, to allow for asymmetry between wage increases and wage declines, with probability $\beta_- \mathrm{d}t$ the worker can pay $\psi^- Z$ units of utility to start bargaining to negotiate a wage cut; workers may prefer a wage cut relative to being laid off. The cumulative distributions for ψ^+ and ψ^- are $\Psi^+(\psi)$ and $\Psi^-(\psi)$ with non-negative support, respectively. Upon renegotiation, the new wage is set by maximizing a Nash Bargaining objective, where the worker's bargaining power is denoted by τ and the outside option in case bargaining fails is the dissolution of the match.[17]

Nominal rigidities in this model only occur with respect to wages of workers within a current match. We assume that wages of new hires are perfectly flexible. The relative flexibility of new hire wages implies that workers can escape their falling real wages on the job when there is a burst of inflation by engaging in costly search for a new match.

Agents' Objectives. Workers born at period t maximize their expected utility and discount the future at rate ρ. They have linear preferences over flow income Y_{it} net of search effort,

[15] We take $\bar{w}_{\pi^*}$ as exogenous and do not attempt to micro-found why there is such a large spike in nominal wage adjustments at 2 or 3 percent. Doing so would be an interesting avenue for future research.

[16] We treat search and renegotiation as two distinct decisions. However, workers could search for another job and bring their external offer back to their original firm to facilitate a wage renegotiation. In this case, the renegotiation costs could stem from costly search. Treating search and renegotiation as two separate decisions facilitates model tractability without changing any of the model's broad conclusions. However, given their potential link, we group them together when decomposing the effects of inflation on worker well-being.

[17] As emphasized by Shimer (2006), the axiomatic foundations of Nash bargaining may fail in search models with on-the-job search as the bargaining set might not be convex. While our numerical simulations suggest bargaining sets are convex in our calibrated model, our wage-setting assumptions can be interpreted in terms of a broader wage-setting protocol because maximizing the Nash bargaining objective in our environment implies that a worker's real wage is reset to the flexible wage of comparable new hires.

$(Y_t - S_t)\mathrm{d}t$, where flow income is equal to the real wage if employed and home production if unemployed. They can pay a stochastic renegotiation cost in utility terms to change their nominal wages $\psi_t Z_t$ as described above. On the other side, firms maximize expected profits and also discount the future at rate ρ. A matched firm's flow profits are given by revenues net of real wages.[18]

3.2. Values and Equilibrium Conditions

Let $J(z,w)$, $U(z)$, and $H(z,w)$ denote the values of firms, unemployed workers, and employed workers, respectively, where w denotes the log-real wage and z denotes the log of worker productivity. Let $\theta(z,w)$ denote the market tightness in the (z,w) submarket where workers search. We now describe the equilibrium conditions.

Free Entry Condition. Free entry implies the complementary slackness condition:

$$\min\left\{Ke^{\phi_k z} - q(\theta(z,w))J(z,w), \theta(z,w)\right\} = 0. \tag{3}$$

Equation 3 imposes a zero-profit condition in each of the open sub-markets where workers are searching and ensures that profits are non-positive in sub-markets where workers are not searching.

Unemployed Workers. The value of being unemployed is characterized by the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned}(\rho+\chi)U(z) = Be^{\phi_b z} + &\underbrace{\gamma_u \partial_z U(z) + \frac{\sigma^2}{2}\partial_z^2 U(z)}_{\text{Law of motion of } z \text{ during unemployment}} \\ &+ \underbrace{\max_{s_u, w_u}\left\{s_u f(\theta(z,w_u))\left(H(z,w_u) - U(z)\right) - e^z \eta_u^{1/\phi_s}\frac{s_u^{1+1/\phi_s}}{1+1/\phi_s}\right\}}_{\text{Expected value of searching for a job}}.\end{aligned} \tag{4}$$

The value function for an unemployed worker consists of three components. First, workers receive the flow value $Be^{\phi_b z}$, which represents their home production or utility from leisure. Second, the function accounts for the evolution of worker productivity during unemployment through the drift term γ_u and diffusion term σ^2. Third, workers derive value from their optimal job search decisions, which involve two key choices: (i) search intensity s_u, which determines how vigorously they look for employment, and (ii) target sub-market w_u, which determines

[18] To improve numerical convergence of the model by smoothing their value functions, we also assume workers of type Z_t face an arbitrarily small stochastic quitting cost and firms face an arbitrarily small stochastic cost of laying off a worker of type Z_t. We suppress the notation for these smoothing parameters in the main text but discuss them more fully in the calibration section of the Online Appendix.

the real wage w_u^* they will receive upon finding employment. The optimal sub-market choice $w_u^*(z)$ is the solution to the following problem

$$w_u^*(z) = \arg\max_{w_u} \left\{ f(\theta(z, w_u)) \left[H(z, w_u) - U(z) \right] \right\}, \tag{5}$$

in which a worker trades off the benefit of finding a job quickly with finding a job that pays a higher wage. Unemployed workers enter the labor market at the bottom rung of their respective job ladders. From the free-entry condition for open sub-markets, the job-finding probability is related to the firm's value. Thus, equation (5) can also be expressed as

$$w_u^*(z) = \max_{w_u^*} \left\{ J(z, w_u)^{1-\alpha} \left(H(z, w_u) - U(z) \right)^{\alpha} \right\}. \tag{6}$$

The optimal search effort of the unemployed $s_u^*(z)$ that solves equation (4) is given by

$$s_u^*(z) = \eta_u^{-1} \left(f(\theta(z, w_u^*(z))) \frac{H(z, w_u^*(z)) - U(z)}{e^z} \right)^{\phi_s}, \tag{7}$$

where η_u^{-1} determines the level of search effort, while ϕ_s captures the elasticity of search effort to the expected value of finding a job.

On-the-Job Renegotiation. When an employed worker pays the bargaining cost, the newly renegotiated wage $w_b^*(z)$ is characterized by the Nash bargaining solution

$$w_b^*(z) = \max_{w_b} \left(J(z, w_b) \right)^{1-\tau} \left(H(z, w_b) - U(z) \right)^{\tau}, \tag{8}$$

which is a weighted average of the firm's and the worker's values with worker bargaining power given by τ. Notice that when $\tau = \alpha$, which is the case in our calibration, the entry real wage of the unemployed worker with productivity z ($w_u^*(z)$ as defined in equation (6)) will be the same as the renegotiated real wage of a worker with productivity z ($w_b^*(z)$ as defined in equation (8)). Thus, when workers choose to renegotiate their wages, they move to the bottom rung of their productivity-specific job ladder.

From the optimal renegotiation decision, we have the renegotiation hazard for a worker of productivity z earning real wage w, $\beta(z, w)$, given by:

$$\begin{aligned} \beta(z, w) = \beta_+ \mathbb{I}_{\{w_b^*(z,w) > w\}} \Psi^+ &\left(\frac{H(z, w_b^*(z, w)) - H(z, w)}{e^z} \right) \\ + \beta_- \mathbb{I}_{\{w_b^*(z,w) < w\}} \Psi^- &\left(\frac{H(z, w_b^*(z, w)) - H(z, w)}{e^z} \right). \end{aligned}$$

Similarly, the new real wage resulting from free adjustments, denoted by $w_{\pi^*}^*(z, w)$, maximizes the same bargaining objective but is subject to the constraint $w_{\pi^*} - w \in [0, 12 \times \pi^*]$.

The Game Between Firms and Employed Workers. We formulate the interaction between matched firms and workers as a dynamic game with Markovian strategies, where we seek a Markov Perfect Equilibrium. In this framework, once a match is formed, the payoff-relevant state variables are limited to the worker's productivity (z) and real wage (w). Given these states, the firm's strategy is to choose whether to lay off the worker or not. We denote by $\mathcal{W}^{j*}$ the set of (z, w) pairs where the firm chooses to continue the match.[19] For each productivity level z, we define $w_l(z)$ as the layoff threshold, which represents the maximum real wage the firm is willing to pay before choosing to terminate the match.

The strategy of a matched worker with productivity z consists of three components: (i) on-the-job search decisions, characterized by search intensity $s_e^*(z, w)$ and target sub-market $w_{jj}^*(z, w)$; (ii) wage renegotiation timing decisions, determining when to pay the renegotiation cost to adjust wages; and (iii) quit decisions, determining the set $\mathcal{W}^{h*}$ of (z, w) pairs where the worker chooses to remain employed. The continuation set for the worker is described by a quitting threshold $w_q(z)$, defined as the greatest lower bound of real wages for which a worker of productivity z is willing to continue the match.

Given these strategies, we define the *continuation set* of the game as the intersection of wages and productivities for which both the firm and the worker are willing to continue the match, $\mathcal{W}^{h*} \cap \mathcal{W}^{j*}$. We assume that $\mathcal{W}^{j*}$ and $\mathcal{W}^{h*}$ are both half-intervals in the real wage dimension with $w_q(z) < w_l(z)$. Consequently, the continuation set at any productivity level z is the interval $(w_q(z), w_l(z))$.

Employed Workers. Within the continuation region of the game, an employed worker's value satisfies the Hamilton-Jacobi-Bellman equation:

$$
\begin{aligned}
\rho H(z,w) = e^w &+ \underbrace{\partial_z H(z,w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 H(z,w) - \partial_w H(z,w)\pi^*}_{\text{Law of motion of } (z,w) \text{ during employment}} \\
&- \underbrace{\delta(H(z,w) - U(z)) - \chi H(z,w)}_{\text{Separation and death shocks}} + \underbrace{\beta_{\pi^*}\left(H(z, w_{\pi^*}^*(w,z)) - H(z,w)\right)}_{\text{Value of free wage adjustment}} \\
&+ \underbrace{\beta_+ \mathbb{I}_{\{w_b^*(z,w) > w\}} \int \max\left\{H(z, w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^+(\mathrm{d}\psi)}_{\text{Net value of costly upward wage adjustment}} \\
&+ \underbrace{\beta_- \mathbb{I}_{\{w_b^*(z,w) \le w\}} \int \max\left\{H(z, w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^-(\mathrm{d}\psi)}_{\text{Net value of costly downward wage adjustment}}
\end{aligned}
$$

[19]As in Blanco, Drenik, et al. (2024), we require the continuation set to be a weakly dominating strategy to ensure the uniqueness of equilibrium.

$$+\underbrace{\max_{s_e,w_{jj}}\left\{s_e f(\theta(z,w_{jj}))\left(H(z,w_{jj})-H(z,w)\right)-e^z\eta_e^{1/\phi_s}\frac{s_e^{1+1/\phi_s}}{1+1/\phi_s}\right\}}_{\text{Expected net value of on-the-job search}}, \tag{9}$$

and for all states where either agent decides to terminate the match, $w \notin (w_q(z), w_l(z))$, the employed worker's value equals the unemployment value $H(z,w) = U(z)$. Additionally, at the boundaries of the continuation set, the standard value-matching condition holds $H(z, w_l(z)) = H(z, w_q(z)) = U(z)$. Finally, since the worker chooses the quitting threshold optimally, the smooth-pasting condition holds at this threshold for both state variables, $\partial_z H(z, w_q(z)) = \partial_z U(z)$ and $\partial_w H(z, w_q(z)) = 0$.

This value function captures several components of worker utility. The first term e^w represents the instantaneous flow value from the current real wage. The next term accounts for the stochastic evolution of the state variables (z, w) and the continuous erosion of real wages due to inflation at rate π^*. The function also incorporates exogenous separation risk δ and mortality risk χ, as well as the option value of free periodic wage adjustments that occur with probability β_{π^*}. The following term captures changes in value due to wage renegotiation. The final term represents the value of on-the-job search, where workers simultaneously choose search intensity and target sub-market. We now describe the optimal policies for these latter two decisions. In particular, the optimal policy for on-the-job search is:

$$w^*_{jj}(z,w) = \arg\max_{w_{jj}}\left\{f(\theta(z,w_{jj}))\left[H(z,w_{jj})-H(z,w)\right]\right\}, \tag{10}$$

where $w^*_{jj}(z,w)$ is the optimal real wage that a worker of productivity z with current real wage w will target when they engage in job-to-job transitions (hence the jj subscript). The optimal policy for on-the-job search can be expressed as follows:

$$s^*_e(z,w) = \eta_e^{-1}\left(f(\theta(z,w^*_{jj}(z,w)))\frac{H(z,w^*_{jj}(z,w))-H(z,w)}{e^z}\right)^{\phi_s}. \tag{11}$$

The policy functions for on-the-job search operate through the same economic mechanisms as those for search during unemployment, with the crucial distinction being that the opportunity cost of finding a new job while employed, $H(z,w)$, depends on the *current real wage*.

Firms. Similarly, the HJB equation for a firm employing a worker at wage w with productivity z in the continuation set of the game is given by

$$\rho J(z,w) = e^z - e^w + \partial_z J(z,w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 J(z,w) - \partial_w J(z,w)\pi^*$$
$$+\beta(z,w)\left(J(w^*_b(z,w),z)-J(z,w)\right)+\beta_{\pi^*}\left(J(z,w^*_{\pi^*}(z,w))-J(z,w)\right)$$

$$- (\delta + \chi + s_e(z,w) f(\theta(z, w^*_{jj}(z,w)))) J(z,w). \tag{12}$$

For $w \notin (w_q(z), w_l(z))$, we have that $J(z,w) = 0$. The corresponding value-matching and smooth-pasting conditions are now given by $J(z, w_l(z)) = J(z, w_q(z)) = \partial_z J(z, w_l(z)) = \partial_w J(z, w_l(z)) = 0$.

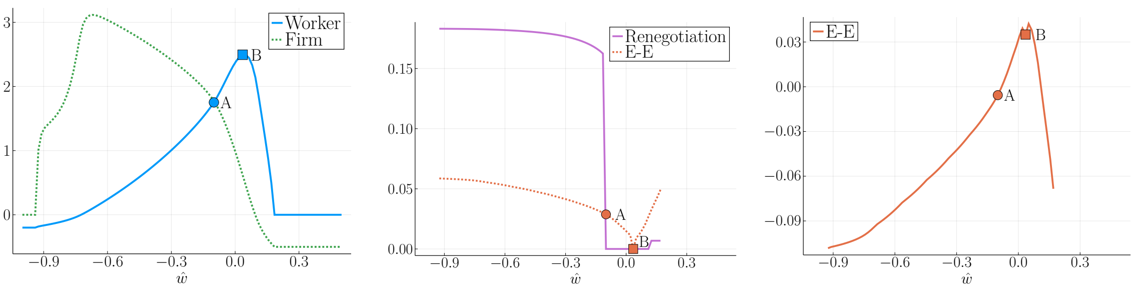
Equilibrium Definition. An equilibrium in this economy consists of a set of value and policy functions for all firms and workers such that: (i) Given the firm's value, the free-entry condition for vacancy posting in all open sub-markets (i.e., equation (3) holds); (ii) Given market tightness, workers' policies during unemployment are optimal (equation (4) holds); (iii) The wage satisfies the Nash bargaining solution (equation (8) holds); (iv) Given the firm's layoff policy and market tightness, workers' on-the-job strategies are optimal (equation (9) holds, with value matching and smooth pasting for $H(z,w)$); and (v) Given employed workers' policies and market tightness, firms' layoff strategies are optimal (equation (12) holds, with value matching and smooth pasting for $J(z,w)$).

3.3. Model Mechanisms in Response to an Unexpected Rise in the Price Level

This section analyzes how individual worker-firm policies respond to an unexpected increase in inflation. We first analyze these responses for a worker with given productivity z. Clearly, the impact of inflation on this worker will depend on the current real wage, which serves as their key state variable. Since what matters for both the worker and the firm is the real wage (w) relative to the worker's productivity (z), we recast the policies of workers and firms as functions of productivity and wage markdowns $\hat{w}$—defined as the log difference between the real wage and productivity, $\hat{w} \equiv w - z$.

Steady State. Figure 3.1 illustrates the values and policy functions for a worker of type z under our baseline parameterization discussed in Section 4 below. Panel A shows the net value of an employed worker of type z relative to unemployment ($H(z,\hat{w}) - U(z)$) and a firm that is matched with that worker ($J(z,\hat{w})$) as a function of their log markdown. Consider the worker value in the solid blue line in Panel A. The circle on this line (labeled with point A) indicates the entry markdown when the worker transitions from unemployment to employment, as defined by equation (5). When a worker starts a job from unemployment, the optimal target markdown implies a positive value for both the firm and the worker. Once employed, markdowns evolve stochastically between the quitting and layoff thresholds, with a negative drift due to both inflation and productivity growth. If the markdown becomes sufficiently high, the firm's profits turn negative and it chooses to lay off the worker. On

Figure 3.1: Values, Hazard Rates and Target Wage Markdown for a Worker of Type Z



Panel A: Worker and Firm Values

Panel B: E-E and Renegotiation Hazard Rates

Panel C: Target Wage Markdown

Notes: Panel A shows the values of an employed worker with given productivity z (net of their unemployment value) and the firm that hires that worker as a function of the markdown, $\hat{w} = w - z$. Panel B shows the renegotiation rate (solid line) and the E-E rate (dashed line) for a worker of productivity z as a function of their markdown. Panel C shows the target wage markdown that a worker of productivity z seeks to obtain when making an E-E transition.

the opposite end, when markdowns become sufficiently low, the value of employment falls below the value of unemployment and the worker opts to quit aiming to find a new job from unemployment with a better entry markdown.

Importantly, the worker's maximum value is attained at a markdown lower than the layoff threshold. We denote this markdown as $\hat{w}^H(z)$, labeled as point B at the peak of the worker value function. There are two forces that generate the non-monotonicity of worker values as a function of the markdown. On one hand, a marginal increase in the markdown raises the flow payoff, thereby increasing the worker's value. On the other hand, it also raises the layoff probability, reducing the worker's expected value. At this optimal markdown from the worker's perspective, the marginal benefit equals the marginal cost. Crucially, if workers had a free opportunity to switch to any job (i.e., without internalizing that higher markdown jobs have lower job finding rates), they would target this optimal markdown. We return to this feature when explaining wage renegotiation and E-E policies below.

The solid purple line in Panel B shows the hazard rate at which workers pay the fixed cost to renegotiate wages with their employer. At point B, workers earn a wage that maximizes their value and have no incentive to renegotiate. Since renegotiation resets wages to the Nash bargaining solution with unemployment as the outside option (equation (8)), wages would be reset to point A in Panel A. Consequently, workers with markdowns between points A and B optimally choose not to renegotiate, as it would lower their wage and value. Once the markdown dips below point A, workers are willing to renegotiate with their employer depending on their draw of the renegotiation menu cost.

The dashed red line in Panel B shows the probability rate of the worker making an E-E transition, given by $s_e(z, \hat{w}) f(\theta(z, \hat{w}^*_{jj}(z, \hat{w})))$ which reflects the worker's search intensity $(s_e(z, \hat{w}))$ and their target markdown at their new employer $(\hat{w}^*_{jj}(z, \hat{w}))$ as defined in equation (11). Again, at point B, workers are at their bliss point and will not engage in any E-E transitions. As wages rise above point B, workers start searching due to increasing layoff risk. Likewise, as wages fall below B, workers start searching to potentially climb their job ladder back towards point B. Importantly, as shown in Panel C, as the markdown falls, the worker becomes willing to switch to employers offering lower starting markdowns. Specifically, all workers who make an E-E transition will choose a starting markdown between points A and B. Since, in searching for a job, workers face the trade-off that—holding search intensity and productivity fixed—jobs with higher wages have lower finding rates, the lower the markdown at the incumbent firm, the more willing workers are to make an E-E transition with a starting markdown closer to point A (equation (10)) in order to transition more quickly to a job with a higher wage. As a result, $\hat{w}^*_{jj}$ falls for job changers as their wage in their incumbent firm falls.

Inflation Effects on Worker Flows, Worker Welfare, and Vacancies. Figure 3.1 provides much of the intuition for how the labor market will respond to an unexpected increase in the price level. An unexpected burst of inflation will decrease the worker's markdown given nominal wages are sticky. All else equal, this *direct* effect of inflation will make all workers worse off by directly reducing their real wage. At the same time, matched firms are made better off from this direct effect, as their profits increase, since they are paying workers of a given productivity less in real terms. Thus, a first-order effect of inflation is to transfer resources away from workers towards firms. But beyond this direct effect, such an inflation shock will also affect worker and firm values by endogenously changing worker flows. Initially, the inflation will move workers further away from their layoff margin, unambiguously decreasing layoffs. Because workers dislike unemployment, inflation also has a *positive* effect on worker welfare by reducing layoff risk.[20] This effect is largest for workers whose initial markdown is to the right of point B. For them, their value of employment increases on net as their

[20] In this sense, our model has an implication where inflation can "grease the wheels of the labor market" by causing real wages to fall and reducing the incentive for firms to fire workers. For related literature, see, for example, Tobin (1972), Card and Hyslop (1997), and Blanco and Drenik (2023).

markdown falls.

However, most workers in our calibrated model have an initial markdown that is to the left of point B. For them, their welfare is strictly reduced from an unexpected burst of inflation. The decreasing markdown induces higher levels of on-the-job search, resulting in a higher E-E transition rate (Panel B). Additionally, for those workers who engage in E-E transitions, it will induce them to search in markets with a lower initial wage markdown (Panel C). Lastly, the higher inflation increases the probability that these workers pay the fixed cost to renegotiate their wage with their existing employers. The declining real wages, increased search effort, and increased renegotiation costs all reduce the welfare of these workers in response to unexpected inflation.

Given these forces at work, we can now answer the question of how an unexpected burst of inflation will affect firm vacancy creation. To further build intuition, let us assume that (i) the worker has an initial markdown to the left of point B and (ii) the number of employed workers who are searching in the new sub-market remains constant before and after the inflation shock. This latter assumption allows us to focus solely on individual worker choices, temporarily abstracting from aggregation. As noted above, the burst of inflation causes these workers to search more in sub-markets that have lower initial markdowns. This response causes firm vacancies to increase for two reasons. To formalize this decision, suppose a worker had an initial markdown of $\hat{w}$ that fell by an amount Δ in response to the unexpected inflation. The total number of vacancies $\mathcal{V}$ posted in the sub-market where this worker of productivity z now searches can be expressed as:

$$\mathcal{V} = \theta(z, \hat{w}_{jj}(z, \hat{w} - \Delta))s(z, \hat{w} - \Delta). \tag{13}$$

Given the properties of the matching function, market tightness within a sub-market—defined by a wage markdown for a worker with a given productivity level—is just the ratio of vacancies $\mathcal{V}$ to worker search effort S. The free entry condition implies that market tightness will remain constant within a given sub-market. Given this, an increase in worker search effort in a sub-market will directly result in an increase in firm vacancies in that sub-market, as shown in the second term of equation (13). By increasing worker search effort, inflation leads to increased vacancies.

However, inflation also has an additional effect on aggregate firm vacancy creation. Given the Cobb-Douglas matching function and the free entry condition, the job-filling rate can be expressed as $q(z, w) = \theta^{-\alpha} = Ke^{\phi_K Z}/J(z, w)$. Using these conditions, equation (13) can be rewritten as:

$$\mathcal{V} = \left(\frac{J(z, \hat{w}_{jj}(z, \hat{w} - \Delta))}{Ke^{\phi_k z}} \right)^{1/\alpha} s(z, \hat{w} - \Delta). \tag{14}$$

As workers of a given productivity shift their search effort to sub-markets with a lower entry markdown in response to inflation, firm value $J(.)$ increases. These sub-markets are more profitable for firms since they offer lower markdowns for a worker of the same productivity and, as a result, they are willing to post more vacancies in these sub-markets. Consequently, these sub-markets have higher vacancies per searcher (i.e., higher market tightness θ). Aggregate vacancies will therefore increase for two reasons in response to an inflationary shock. First, more workers will be searching overall, which will increase vacancies in all sub-markets where search effort increases. Second, there will also be a systematic shift towards sub-markets that have higher job-finding rates and lower job-filling rates. Both forces cause aggregate vacancies to rise in response to an unexpected burst of inflation. The expected duration of vacancies, measured by the inverse of the job-filling rate, will also increase in response to an inflationary shock. In our quantification below, we show these results hold in the aggregate since the share of workers with markdowns to the right of point B is only a small fraction of all workers.

4 Quantifying the Model

In this section, we discuss our calibration of the model parameters. The time period in our model is a month. We calibrate the model using the simulated method of moments (SMM) approach, targeting several moments of the microdata. The Online Appendix contains further details on the construction of moments, a sensitivity analysis following the procedure in Andrews, Gentzkow, and Shapiro (2017), and robustness to alternative parameter values.

4.1. Fixed Parameters

Table 1 shows the parameters that we set externally. We set the monthly discount factor ρ to 0.005, consistent with an annual discount rate of 6% (Hall, 2017). The death rate χ is calibrated to an annual rate of 5% per year to match the 85th percentile of the expected labor market experience distribution of 40 years (Durante et al., 2017). We set the steady state trend inflation π^* to 2.2% annually, consistent with the observed inflation dynamics during the post-2000 period within the United States. Likewise, we also set the upper bound of the free nominal wage adjustment process, $\Delta\bar{w}_{\pi^*}$, to 2.2% annually. The elasticity of the matching function α is set to the standard value of 0.5, following Petrongolo and Pissarides

(2001). We also set the worker's bargaining power, τ, equal to the elasticity of the matching function. This assumption implies that the entry wage markdown is equal to the incumbent workers' markdown following renegotiation. Finally, we normalize the mean of the initial productivity distribution, μ_{z0}, to zero and the search cost scale parameter for the unemployed, η_u, to one.

Table 1: Fixed Parameters

Parameter	Description	Value	Target
ρ	Discount factor	0.005	Annual discount rate of 6%
χ	Death rate	0.004	85th perc. of experience dist.
μ_{z0}	Mean of initial productivity	0.0	Normalization
η_u	Search cost scale when unemployed	1.0	Normalization
α	Elast. of the matching function	0.5	Standard value
τ	Worker's bargaining power	0.5	Standard value
$\Delta\bar{w}_{pi^*}$	Trend inflation	0.002	Annual inflation rate 2016-2019
π^*	Target inflation	0.002	Annual inflation rate 2016-2019

Notes: The table lists the values of model parameters externally set and their sources.

4.2. Calibrated Parameters

Table 2 shows the set of parameters that we calibrate, along with their calibrated values. To calibrate these parameters, we target a series of empirical moments on the evolution of wages over the life cycle, worker flows in the aggregate and across the income distribution, and the nominal wage adjustment process reported in Grigsby, Hurst, and Yildirmaz (2021). Below, we discuss how these targets are jointly used to calibrate the model parameters.

Productivity process. σ_{z0} is chosen to match a P90-P50 weekly earnings ratio for workers aged 25-27 of 2.02 between 2016 and 2019 from the CPS.[21] For productivity dynamics, we set the productivity drift while employed to $\gamma_e = 0.002$ per month to capture a 70 percent growth rate in average earnings of employed workers over 30 years (Alves and Giovanni L Violante, 2025). The negative drift for the unemployed $\gamma_u = -0.006$ matches the elasticity of wage changes between consecutive jobs with respect to the length of the intervening unemployment spell, as estimated by Jarosch (2023). The standard deviation of productivity shocks, σ, is set to 0.033 to match the P90-P50 weekly earnings ratio for workers aged 25-55.

[21] Our focus on the P90–P50 ratio, both here and for initial skill dispersion, reflects that top-end earnings inequality primarily reflects differences in human capital and skills, whereas bottom-end variation is more heavily influenced by heterogeneity in labor supply at the extensive margin (see Alves and Giovanni L Violante, 2025, for a similar approach).

Table 2: Internally Calibrated Model Parameters

Parameter	Description	Value
Productivity Process		
γ_e	Productivity drift for employed	0.002
γ_u	Productivity drift for unemployed	-0.006
σ	Std. dev. of productivity shock	0.033
σ_{z0}	Std. of initial productivity	0.559
Labor Market Flows		
B	Non-employment production	1.087
ϕ_b	Elast. of unemp. income wrt. z	0.722
K	Vacancy cost	9.71
ϕ_k	Elast. of vacancy cost wrt. z	1.453
η_e	Search cost scale when employed	5.405
ϕ_s	Elast. of search cost	0.095
Exogenous Separations		
δ_0	Exog. separation rate function	0.005
δ_1	Exog. separation rate function	0.019
δ_2	Exog. separation rate function	-2.295
Nominal Wage Adjustment		
β_{π^*}	Prob. of free wage adjustment	0.083
β_+	Prob. of positive wage renegotiation	0.184
β_-	Prob. of negative wage renegotiation	0.007
λ	Prob. mass at zero for menu cost dist.	0.864
ζ	Scale parameter of menu cost dist.	0.647

Notes: The table lists the values of model parameters internally set.

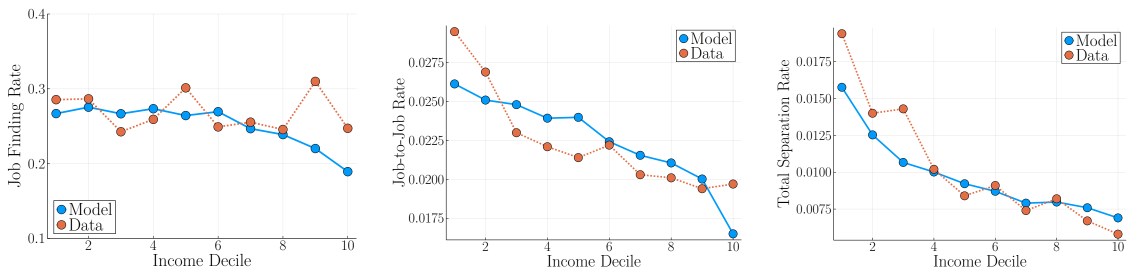
Exogenous Separations. In the model, separation into unemployment results from endogenous choices and exogenous shocks $\delta(Z)$. We discipline the exogenous separation process by using data from the 2016-2019 CPS, where unemployed respondents are asked the reason they became unemployed. Possible answers to this question include whether the worker was a "job leaver" (e.g., quits), whether they were a "job loser/on layoff" (e.g., layoffs), or whether they were unemployed for other reasons, such as being an "other job loser" or whether their "temporary job ended". We map quits and layoffs in the CPS to the endogenous quits and endogenous layoffs in the model. In the CPS during the 2016-2019 period, roughly 17%, 22%, and 61% of the unemployed reported that their unemployment spell originated from a quit, a layoff, or another reason, respectively. We interpret separations due to other reasons as the data analog of exogenous separations $\delta(Z)$ within the model. We parameterize the relationship between exogenous separations and worker productivity with the following functional form $\delta(Z) = \delta_0 + \delta_1 \exp(\delta_2 Z)$. To set these three parameters, we follow an indirect-inference approach and target the separation rate into unemployment due to "other reasons" across the earnings distribution prior to the separation. As shown in Panel C of Figure 4.1, exogenous separations fall sharply with respect to worker earnings.

Endogenous Labor Market Flows. Our goal is to replicate not only aggregate endogenous flows but also flows throughout the income distribution. The ability of unemployed workers to find jobs is determined by their search effort and their job-finding rate per efficiency unit of search. We calibrate the search cost of the employed η_e and the average vacancy posting cost K to match the aggregate average E-E and U-E transition rates from the CPS data during the 2016-2019 period. Additionally, following Faberman et al. (2022), we set the elasticity parameter ϕ_s in the search cost function to match the estimated search effort-wage elasticity of -0.52 (based on hours spent searching) in their survey data, which is obtained by regressing log search effort on log real income and replacing their controls for worker characteristics with worker fixed effects in the model regression. To match the average endogenous separation rate given by the sum of quits and layoffs (endogenous E-U flows), we exploit the fact that a larger level of home production B raises the opportunity cost of employment and pushes up the wages that workers search for during unemployment, which gets them closer to the layoff threshold. The calibrated value of B implies a ratio of average home production among the unemployed to average production among the employed of 58%, which is in the range reported by Chodorow-Reich and Karabarbounis (2016).

Two parameters play an important role in shaping the heterogeneity of labor market flows in the data: ϕ_k and ϕ_b, which determine how vacancy posting costs and home production of the unemployed scale with workers' productivity, respectively. These parameters also govern how labor market flows will respond differentially throughout the income distribution in response to an unexpected shock to the price level. The dashed red lines in Panels A and B of Figure 4.1 use CPS data from the 2016-2019 period to show how U-E rates and E-E rates differ across the income distribution. These patterns identify ϕ_k and ϕ_b.

Through the lens of the model, the fact that E-E rates decline with income is indicative that the vacancy cost of hiring more productive workers is higher *relative* to their productivity ($\phi_k > 1$); high wage workers churn less while employed in part because we estimate that it is expensive for firms to hire them. The extent to which the U-E rate varies with income helps to pin down ϕ_b. If it is more expensive to hire a high productivity worker, we would expect the U-E rate to also decline with income. However, in the data, the U-E rate is relatively constant with income. The calibration rationalizes this pattern by estimating that $\phi_b < 1$. A value of $\phi_b < 1$ implies that more productive workers lose more—in relative terms—by staying in the unemployment state, which incentivizes them to search more intensively while

Figure 4.1: Targeted Moments: Flows in the Labor Market



Panel A: U-E Rate Panel B: E-E Rate Panel C: E-U Rate

Notes: The figure shows the U-E rate, E-E rate and E-U rate both in the data (dashed line) and as predicted by the calibrated model (solid line).

unemployed, despite facing greater difficulty finding jobs due to the higher costs firms incur when hiring them. As seen from Figure 4.1, our calibration (blue lines) matches closely both the level and cross-income variation of U-E flows, E-E flows, and E-U flows from the CPS data (dashed red lines).

Nominal Wage Adjustments. We parameterize how wages adjust on the job using the moments provided in Grigsby, Hurst, and Yildirmaz (2021) who use data from the payroll processing firm ADP to measure wage adjustments for U.S. workers during the 2008-2016 period. The Calvo parameter β_{π^*} governs the arrival rate of costless wage changes between 0 and $\Delta\bar{w}_{\pi^*}$. This process helps us match the large spike in wage changes at 0 and 2-3% with a missing mass in between. We set β_{π^*} to a monthly arrival rate of 0.083 to reflect common human resource practices that nominal wages have the opportunity to adjust costlessly once a year. The parameters β_+ and β_- directly inform the frequency of positive and negative wage changes, respectively. The former is calibrated to 0.184, implying an actual monthly frequency of positive wage changes of 6.4%, consistent with the moments provided in Grigsby, Hurst, and Yildirmaz (2021). The value of the latter is much lower, implying that opportunities to bargain wage cuts rarely arrive, which is necessary to match the observed small share of negative wage changes found in Grigsby, Hurst, and Yildirmaz (2021). The heterogeneous menu cost part of the model helps us match the long tail in wage changes of job-stayers above 2%. Conditional on $\beta_+ dt$, the renegotiation cost for workers increasing their wage is then drawn from the distribution Ψ^+, which we model as an exponential distribution with a mass point at zero. We define ζ as the scale parameter of the exponential distribution, while the parameter λ governs the size of the mass point at zero.[22] λ and ζ are parameterized to match the share of small versus large wage changes in the ADP data.

Targeted and Untargeted Moments. Table 3 shows how our model matches the targeted moments for the wage change distribution, the income distribution over the life cycle, and various labor market flow elasticities. The goodness of fit for the labor market flows was discussed in Figure 4.1 above.

Table 3: Comparison of Targeted Moments between Model and Data

Moment	**Data**	**Model**
Frequency of on-the-job wage decreases	0.004	0.0
Frequency of on-the-job wage increases	0.063	0.064
Share $\Delta w_b \in (0, 6)/(0, \infty)$	0.73	0.73
Share $\Delta w_b \in [6, 11)/(0, \infty)$	0.14	0.16
Share $\Delta w_b \in [11, \infty)/(0, \infty)$	0.13	0.12
Search effort-wage elasticity	-0.52	-0.54
P90/P50 real wages (age 25)	2.02	2.02
P90/P50 real wages (ages 25-55)	2.33	2.35
Avg. 30-year wage growth	0.7	0.71
New wage-unemployment length elasticity	-0.006	-0.006

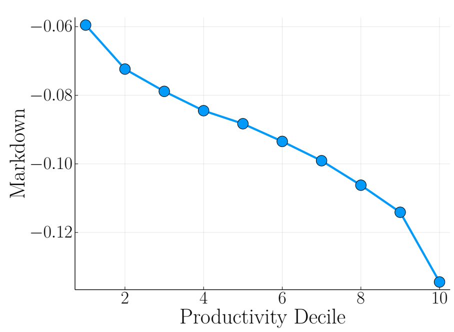
Notes: The table shows the set of moments (excluding the labor market flows, the results for which are reported in Figure 4.1) that were targeted for calibration.

Figure 4.2 shows that our model also matches two untargeted moments. First, given our estimates of ϕ_b and ϕ_k, our model also implies a negative relationship between markdowns and productivity as shown in Panel A. Lower productivity workers are more elastic and, as a result, experience lower wage markdowns on average. This prediction of our model aligns well with the findings of Chan et al. (2023) using Danish microdata and Volpe (2024) using Norwegian microdata; both document that lower productivity workers face smaller wage markdowns. Panel B shows that our model matches well the distribution of nominal wage changes, conditional on a positive change, found in the ADP data. We target that only 6% of job-stayers receive a wage change during a given month. Our model matches that moment (row 2 of Table 3). We also target the fraction of wage changes that are between 0 and 6%, between 6% and 11%, and between 11% and infinity. Despite this crude calibration, Panel

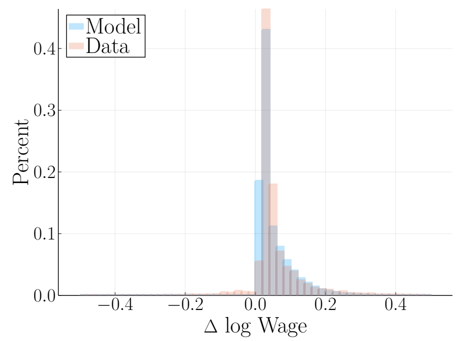
[22] Similar to the modeling of menu costs in the pricing literature as in Nakamura and Steinsson (2010) and Alvarez, Le Bihan, and Lippi (2016), the mass point at zero allows us to match the continuously declining probability of larger nominal wage changes beyond 2-3%.

B of Figure 4.2 shows that the model matches well the full distribution of nominal wage changes conditional on a positive change occurring. For example, our model generates the large spike in nominal wage changes at 2% as seen in the data.

Figure 4.2: Untargeted Moments: Markdowns and the Distribution of Wage Changes



Panel A: Markdowns



Panel B: (Non-zero) Wage Changes

Notes: Panel A shows the average markdowns (defined as log real wage minus productivity) by productivity decile in the equilibrium of our model. Panel B shows the distribution of non-zero wage changes for job-stayers in the model.

5 How Workers Respond to Temporary Changes in Inflation

In this section, we analyze how labor market flows, the vacancy-to-unemployment rate, wages, and worker welfare respond to a temporary shock to the inflation rate. We start by exploring a one-time unexpected increase in the price level of 13.5%, all else equal. The 13.5% increase represents roughly the jump in the U.S. price level during the April 2021 and May 2023 period. This experiment allows us to assess the dynamics of flows and wages to a one-time shock separately from the dynamics of the shock. Doing so allows us to better understand the model mechanisms and dynamics.

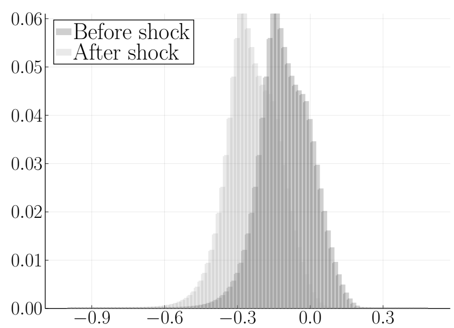
Our second exercise explores how wages and labor market flows respond to a series of unexpected inflation shocks that replicate the actual inflation path observed during the 2021-2024 period. Throughout this period, we impose that workers consistently maintain expectations of 2.2% annual inflation going forward, implying that in each period, the realized inflation rate is an unexpected surprise. This counterfactual allows us to better assess how the model matches the actual time series dynamics of labor market outcomes observed during this period. We conclude this section by quantifying the welfare effects for different types of workers under both counterfactual scenarios.

5.1. Counterfactual 1: One-Time Unexpected Increase in the Price-Level

We begin by assessing how an unexpected one-time increase in the price level of 13.5% affects the dynamics of labor market flows and wages.

5.1.1. Wage Markdowns On Impact. Panel A of Figure 5.1 shows the distribution of wage markdowns in the economy right before (in dark gray) and right after (in light gray) the temporary inflation shock. Given the nominal wage rigidity, an unexpected jump in the price level of 13.5% results in the wage markdown decreasing for all workers by 13.5 percentage points upon impact. As discussed above, the overwhelming majority of workers have initial markdowns to the left of point B in our illustrative example in Figure 3.1.

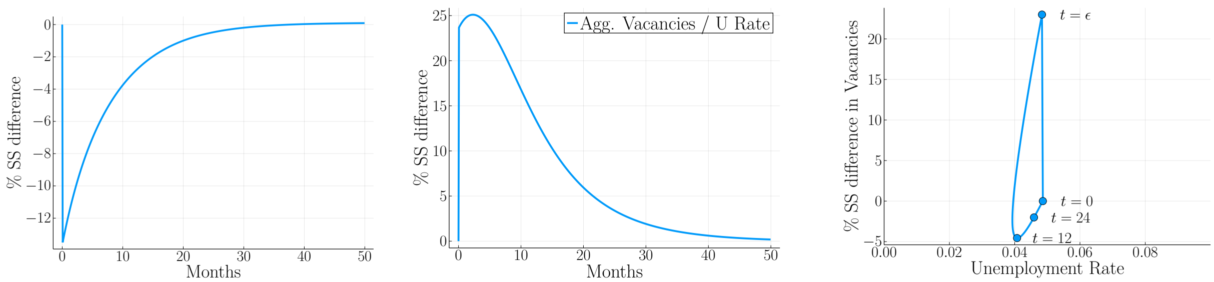
Figure 5.1: Markdown Distribution



Notes: Figure shows the distribution of wage markdowns right before and right after the unexpected increase in the price level.

5.1.2. Aggregate Wage and Worker Flow Dynamics. We motivated the paper by pointing out the puzzle that during the inflation period, the vacancy-to-unemployment rate was at historically high levels while real wages were falling sharply. Figure 5.2 plots the model implied dynamics of aggregate real wages (panel A), the vacancy-to-unemployment rate (panel B) and the corresponding Beveridge curve (panel C) in response to the unexpected 13.5% increase in the price level through the lens of our model. Upon impact, real wages fall by 13.5% given the nominal wage rigidity. However, within about 30 months, real wages return to their steady-state path. The real wage declines are accompanied by a large increase in the vacancy-to-unemployment rate upon impact, as in the data. Given the small movements in the unemployment rate, essentially all of the increase in the V/U ratio is driven by an increase in vacancies. The V/U ratio also returns to steady-state levels within about 30 months.

Figure 5.2: Real Wage, V/U Ratio, and the Beveridge curve



Panel A: Real Wage Panel B: V/U Ratio Panel C: Beveridge curve

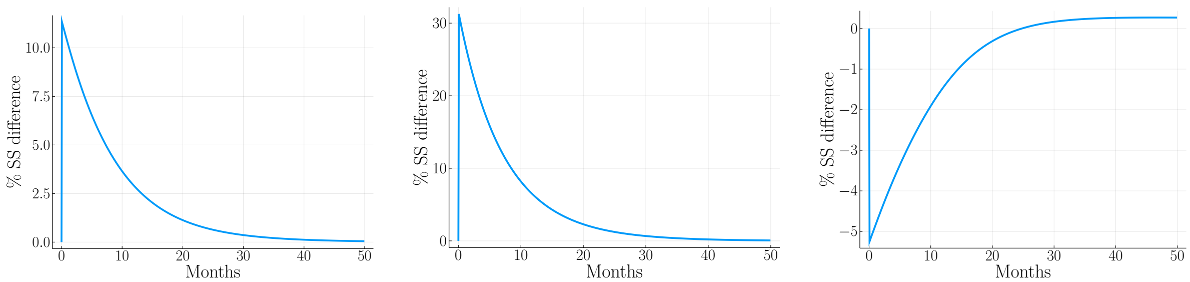
Notes: Panels A and B show the time series response of aggregate log real wage and the vacancy-to-unemployment rate, respectively, in response to the unexpected price level increase. Panel C shows the dynamics of the Beveridge curve in response to the same shock.

These findings illustrate three key results. First, our model shows that an unexpected burst of inflation causally generates a decline in real wages and an increase in the vacancy to unemployment rate without any other underlying labor market shocks, matching key empirical regularities of the U.S. labor market during the 2021-2024 period. Second, the model implies meaningful dynamics in that the one-time shock to the price level causes real wages to be below steady-state levels for just under three years. Finally, our model highlights how the Beveridge curve can systematically shift upward during periods of inflation, all else equal.[23]

Figures 5.3 and 5.4 show the underlying mechanisms within our model that generate the rise in vacancies in response to a burst of inflation. As highlighted in Section 3.3, a combination of a rise in E-E flows, coupled with the free entry condition on vacancies, incentivizes firms to post more vacancies when workers are searching more. Additionally, searching workers during inflationary periods will systematically sort into markets with a lower offered wage and a higher job-finding rate; workers making E-E transitions will systematically enter their new job ladder on a lower real wage rung during inflation periods. Panels A, B, and C of Figure 5.3 show the average worker search effort, the E-E transition rate, and the entry wage during E-E transitions after the 13.5% increase in the price level. Upon impact,

[23]The shifting Beveridge curve also highlights the difference between this model and benchmark sticky wage models such as the one in Galı (2015), where wage inflation and unemployment are negatively correlated through a conventional Phillips curve. In such a model, a temporary burst of inflation would be mirrored by changes in unemployment, whereas here, a substantial part of the response is through an increase in the aggregate vacancy-to-unemployment rate rather than a change in unemployment.

Figure 5.3: Employed Search Effort, E-E Rate, and Initial Markdown of Job-Changers



Panel A: Search Intensity of Employed

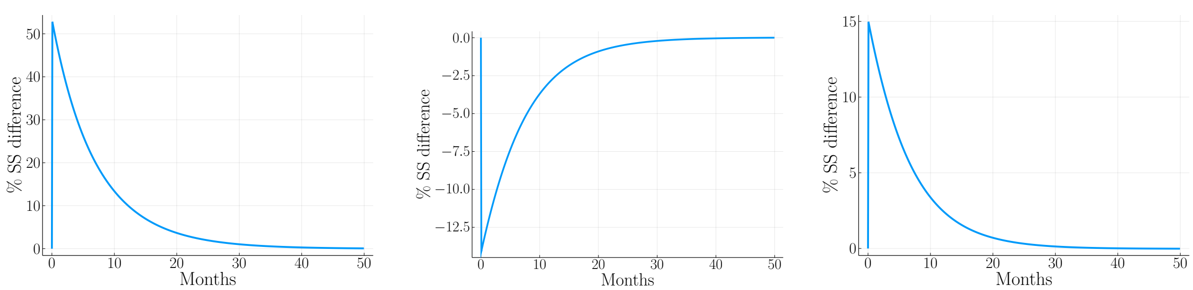
Panel B: E-E Rate

Panel C: Starting Markdown of Job-Changers

Notes: Figure shows the search effort the employed, the E-E rate, and the starting markdown of job-changers, respectively, in response to the one-time unexpected change in the price-level. All panels are reported as percent deviation from the steady-state.

the average workers' search effort increases by about 11%, the E-E rate increases by about 30%, and the entry real wage of workers making E-E flows falls by about 5% relative to their steady-state values.

Figure 5.4: E-E Vacancies, Vacancy Filling Rate, and Vacancy Duration



Panel A: E-E Vacancies

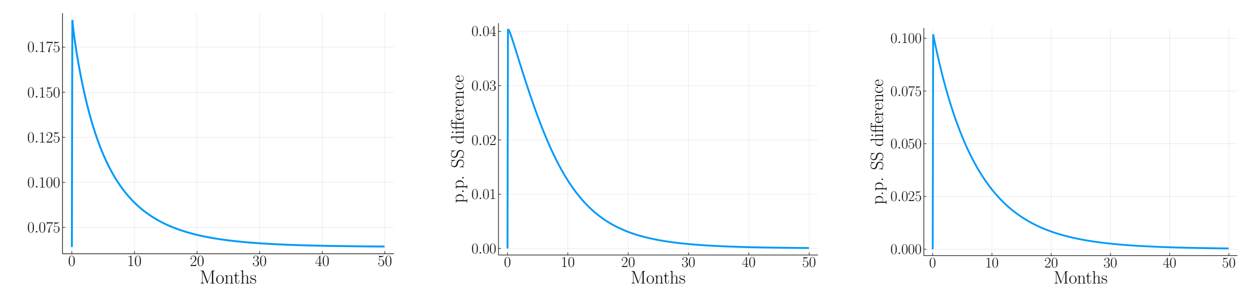
Panel B: E-E Vacancy Filling Rate

Panel C: E-E Vacancy Duration

Notes: Panel A shows the time series response of E-E vacancies in response to the unexpected price level increase. Panels B and C show the time series response of the E-E vacancy filling rate and E-E vacancy duration, respectively, in response to the same shock. All panels are reported as percent deviation from the steady-state.

Figure 5.4 shows the response of vacancies created for workers making on-the-job transitions (Panel A), the E-E vacancy filling rate from the firm's perspective (Panel B) and the duration of E-E vacancies (Panel C). On impact, vacancies for E-E workers increase by 50% relative to their steady-state value.[24] As discussed in Section 3.3, the corresponding increase in vacancies associated with increasing E-E flows results in the firm's E-E job-filling rate falling and the duration of E-E vacancies rising. These findings are consistent with both the empirical finding that vacancy durations increased sharply during the recent inflation period and with the fact that U.S. firms reported difficulties in hiring workers during late 2021 and 2022.[25]

Figure 5.5: Frequency of Wage Increases and Wage Changes of Job Stayers and Changers



Panel A: Monthly Freq. of Wage Increases | Panel B: Wage Changes of Job Stayers | Panel C: Wage Changes of Job Changers

Notes: Panel A shows the time series response of the frequency of monthly wage changes for job stayers in response to the unexpected price level increase. Panels B and C show the time series response of wage changes for job stayers and job changers, respectively, in response to the same shock.

While there is a large increase in E-E flows induced by inflation, most workers still remain with their original employer. Some of these workers chose to pay the fixed cost to renegotiate their nominal wage. Panel A of Figure 5.5 shows that, in response to inflation, the frequency of wage increases for job-stayers jumped by 12 percentage points (from 6% per month to around 18% per month). In addition, the average nominal wage change of job-stayers, conditional on a change, increased by about 4 percentage points in response to the inflation shock. Panel C also shows the analogous nominal wage change of job-changers in response to inflation. The nominal wages of job-changers increased by about 10 percentage points after the unexpected price level increase. This increase was less than the 13.5% inflation shock

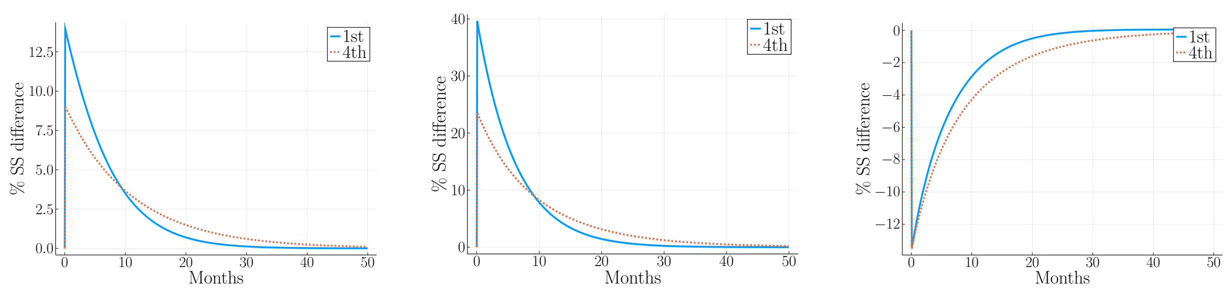
[24] In the Online Appendix, we show that our model generates no change in the U-E rate in either counterfactual 1 (Figure B.16) or counterfactual 2 (Figure B.17) because both the value of not working and the new hire wage are in real terms and are therefore not affected by changes in the price level. Appendix Figure B.17 also shows that the layoff rate fell, on average, by about 30% over the two years after the inflation shock started under counterfactual 2. The comparable number in the data was about 20%.

[25] In Online Appendix Figure B.13, we follow the empirical methodology in Davis, Faberman, and Haltiwanger (2013) to show that the duration of vacancies did, in fact, increase sharply during the inflation period.

because job-changers start searching in markets with lower wage markdowns ($\hat{w}$) on average (as shown in Panel C of Figure 5.3). The model, therefore, replicates the empirical finding that the gap between the wage changes of job-changers and the wage change of job-stayers increased sharply during the recent inflationary period.

5.1.3. Disaggregated Wage and Worker Flow Dynamics. Figure 5.6 shows the time series pattern of job search, E-E flows, and real wages for workers at the top and bottom income quartiles within our model. Upon impact, lower productivity workers (1st quartile) increase their on-the-job search (Panel A) and, as a result, their job-to-job flows (Panel B) more than higher wage (productivity) workers. With the one-time shock, the difference in search behavior and E-E flows between the two groups upon impact is large. Because low-wage workers search more in response to inflation, their real wages recover more quickly (Panel C). In response to the one-time 13.5% unexpected price level shock, the real wages of bottom quartile workers recover within two years, with most of the gain occurring in the first twelve months. The real wages of top quartile workers, however, take almost four years to fully recover. High-wage workers, therefore, have elevated on-the-job search—and subsequent E-E flows—for a much larger period of time than low-wage workers. We view it as a strength of our calibrated model that it replicates empirical labor market patterns for both the aggregate time series and separately for different wage quartiles during the recent inflationary period.

Figure 5.6: Heterogeneity in Job Search Effort, E-E Rate, and Real Wages



Panel A: Job Search by Productivity Quartiles

Panel B: E-E Rate by Productivity Quartiles

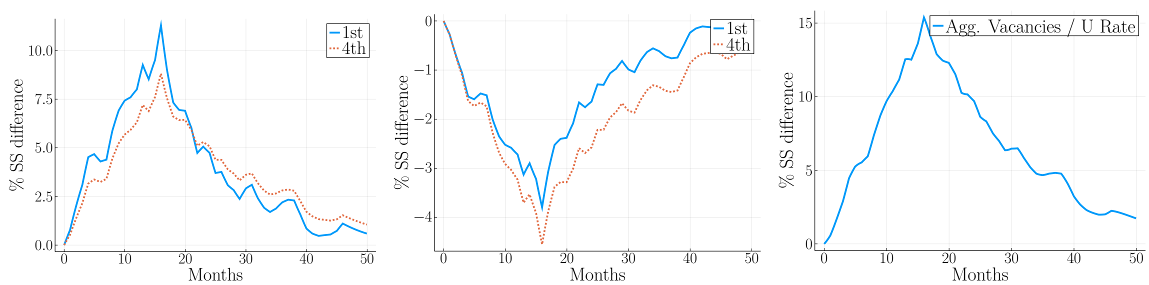
Panel C: Real Wages by Productivity Quartiles

Notes: The figure shows the time series response of the job search effort, E-E rate, and real wages for workers in the bottom productivity quartile (solid blue line) and for workers in the top productivity quartile (dashed red line) in response to the unexpected price level increase.

5.2. Counterfactual 2: Series of Unexpected Price Level Shocks

In this subsection, we feed in a series of unexpected price level shocks to match the actual time path of price level changes in the U.S. data during the period from April 2021 through December 2024. This counterfactual is designed to better match quantitatively how inflation has affected the time path of various labor market outcomes. As a result, we compare the model predictions of this counterfactual to the empirical patterns documented in Section 2.

Figure 5.7: E-E Rate, Real Wages and V/U Ratio



Panel A: E-E Rate   Panel B: Real Wages   Panel C: V/U Ratio

Notes: Figure shows the time series response of E-E rates (Panel A), real wages (Panel B), and vacancy-to-unemployment ratio (Panel C) for top (4th) and bottom (1st) quartiles of productivity in response to a series of unexpected price level shocks that match the inflation dynamics during the March 2021 to December 2024 period.

Panel A of Figure 5.7 shows the model implied response of E-E flows is roughly consistent with its empirical counterpart. For example, about 15 months after the inflation period started—which would be mid-2022—our model predicts that the E-E rate increased by 8-10% for both low- and high-wage workers relative to their steady-state levels. As seen from the data analog in Figure 2.2, the E-E rate for the overall economy increased from a rate of 2.24 percent per month in the pre-period to a rate of 2.57 percent per month in June 2022—a roughly 10% increase. Moreover, the quantitative predictions of our second counterfactual are also close to the survey responses reported in Stantcheva (2024). In particular, Stantcheva (2024) finds that roughly 9% of the workers in her survey reported that they actually changed jobs as a result of the recent inflation. The total additional E-E flows implied by our model in response to the recent inflation—which is calculated by integrating over the time paths shown in Panel A—is an additional 4.6 percent of employed workers.

Panel B shows that our model implies that the recent inflation caused real wages of high- and low-wage workers to fall by about 4.5% and 3.5% relative to trend, respectively, as of mid-2022. Empirically, as shown in Figure 2.4, real wages fell by -5% and -3% for high- and low-wage workers in non-WFH sectors as of mid-2022. However, our model does not match the persistent decline in real wages observed in the data, as the inflation rate returned to steady-state levels. For example, as of December 2024, real wages for workers in non-WFH occupations were still 4% and 2% depressed relative to trend for high- and low-wage workers, according to the Atlanta Fed Wage Tracker. Our model implies that after 45 months, real wages for both groups should be almost back to their pre-trend levels.

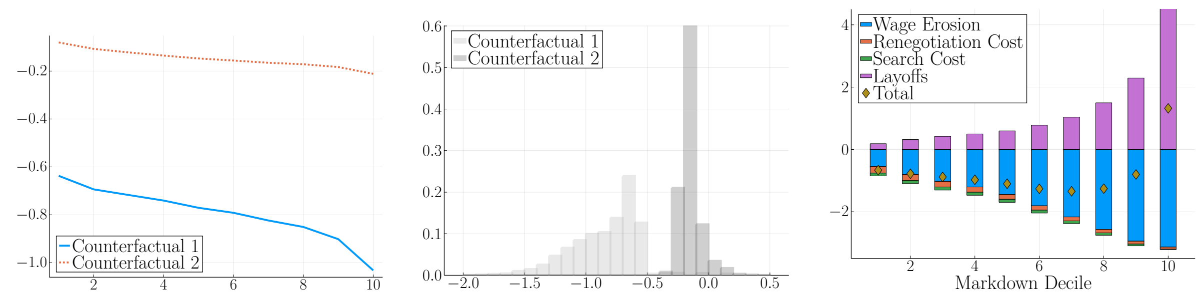
Panel C shows that our model implies that the vacancy-to-unemployment rate should have increased by 15% relative to its steady-state value as of mid-2022. The vacancy-to-unemployment rate actually increased by over 60% between late 2019 and mid-2022. As a result, our model is underpredicting the rise in vacancies observed in the data. A likely reason for this is that, while our model is rich in many dimensions, we are missing a key mechanism that can amplify the vacancy response. If there is a fixed sunk cost to posting an initial vacancy, replacement hiring can be an important component of labor market flows.[26] Incorporating a notion of replacement hiring could amplify the vacancy response from an inflationary shock. In fact, Bagga et al. (2025) find that some notion of replacement hiring is needed to match the vacancy dynamics during the post-pandemic period in response to a shift towards working-from-home. Our framework shows that unexpected inflation can lead to a burst of vacancy creation, even without any replacement hiring. However, we acknowledge that omitting such a mechanism results in our model underpredicting the actual empirical rise in vacancies observed during the inflation period.

5.3. Worker Welfare

Panel A of Figure 5.8 shows the welfare response of workers across different initial wage deciles under our two counterfactual scenarios. We measure the welfare costs to workers in consumption equivalent units (in multiples of monthly real income before the shock); a welfare cost of 1.0 means a worker would be willing to give up one month of their pre-shock real wage to avoid the temporary increase in inflation. As seen from the figure, workers in all productivity deciles experience welfare losses due to the unexpected increase in the price level under both counterfactuals, with higher-productivity workers consistently suffering larger

[26] For a discussion of how unfilled vacancies can retain positive value in equilibrium even under free entry, see, for example, Fujita and Ramey (2007) and Hornstein, Krusell, and Giovanni L. Violante (2007). Both Elsby et al. (2025) and Mercan and Schoefer (2020) show that replacement hiring, which results from a fixed sunk cost associated with posting a vacancy, is an important component of total vacancies, particularly during periods when there is significant worker churn due to quits.

Figure 5.8: Welfare Loss from Recent Inflation, in Units of One Month's Consumption



Panel A: Welfare Change by Income

Panel B: Welfare Distribution

Panel C: Welfare Decomposition

Notes: Panel A of the figure shows the welfare cost of the unexpected inflation shock for workers in different deciles of the worker income distribution under our two counterfactual scenarios. Results are shown in consumption equivalent units of monthly income. Panel B of the figure shows the distribution of welfare changes for all workers under both counterfactuals. The x-axis for this panel is again in consumption equivalent units of monthly income. Panel C shows the decomposition of welfare losses by markdown decile into its various components four counterfactual 1.

losses than lower-productivity workers. Under the one-time shock scenario (counterfactual 1, solid blue line) the average worker experiences a welfare loss equal to approximately 80% of one month's income.

While counterfactual 1 primarily serves to illustrate the model's mechanisms, we consider the welfare results from counterfactual 2 (dashed red line) to provide a more accurate assessment of the actual welfare costs incurred during the recent inflation period. In this scenario, the average worker lost approximately one-fifth of monthly earnings due to inflation's effects in our sticky-wage model. For context, the median worker has an average annual real income of about \$60,000 during this period, implying that recent inflation reduced the welfare of the median worker by about \$1000. This is also a very sizable number. Given that there are about 150 million workers in the U.S. labor market, the total loss to workers from the recent inflation was over \$150 billion. As we show below, a substantial portion of these losses translates into gains for firms. Although we do not explicitly model firm ownership, incorporating this feature would moderate the losses for higher-income workers who typically hold the majority of firm equity.

Panel B reveals substantial heterogeneity in welfare losses underlying the patterns in Panel A. Consider the distribution of welfare losses from counterfactual 2, as shown in the darker gray bars. Some workers lost over half of one month's income in consumption equivalent terms, while others lost hardly anything. This variation is larger than the variation across income groups shown in Panel A. What drives the additional variation? The answer lies in the model mechanisms described in Section 3.3. For workers whose initial wage is to the right of point B on the worker value line in Figure 3.1, a burst of inflation can actually be welfare-increasing because it moves them further away from the layoff threshold. Specifically, inflation shifts their markdown from a point to the right of point B, close to the layoff threshold, to a point closer to point B, reducing their layoff risk. Consequently, workers initially close to the layoff threshold are the ones with the smallest welfare losses—or even welfare gains—in Panel B of Figure 5.8. There are very few workers close to the layoff margin in our calibration, but these are the ones with the welfare changes close to zero. Conversely, workers with the largest welfare losses are the unlucky workers who failed to receive a nominal wage adjustment, either because they did not receive a free wage adjustment opportunity or because they drew very large renegotiation costs.

With this in mind, the welfare effects for employed workers can be decomposed into four components: (i) workers receive real wage declines due to sticky wages in response to the inflation increase and their limited mobility across employers, (ii) workers have to incur search costs to increase their wages at other firms, (iii) workers have to incur renegotiation costs to increase their wages at their current firm, and (iv) workers benefit from lower layoff risk. Panel C of Figure 5.8 shows the decomposition of welfare losses for workers of differing initial wage markdown under our first counterfactual. We focus on this scenario because it provides the intuition behind the model mechanisms discussed above. The diamonds positioned within each bar represent the total welfare effects, while the blue portion of the bars represents the direct effects of the real wage declines, the purple area represents the welfare gains from the declining layoff margin, and the green and orange areas represent the welfare losses from the incurred search and renegotiation costs, respectively.

Consistent with our discussion above, the welfare gains from the reduced layoff margins are largest for workers with the highest initial markdowns (top decile). These are the workers who are closest to the layoff margin. The markdown deciles are drawn based on the ex-ante markdown before the inflation shock, but the idiosyncratic productivity shocks move workers across the markdown distribution ex-post. Thus, all ex-ante markdown deciles derive some benefit from moving away from the layoff margin. The welfare losses from the increased search and renegotiation are small but not negligible. The welfare loss incurred by the median worker from the sum of the renegotiation and search costs in counterfactual 1 is approximately 20%

of the total welfare loss. This percentage is similar to what we estimate from counterfactual 2, where 20% of the total welfare loss for the median worker is also attributed to increased search and renegotiation costs.

5.4. Parameter Robustness, Alternate Mechanisms and Further Discussion

In this subsection, we provide a brief summary of the robustness of our results to different parameters, summarize how other shocks would affect labor market dynamics through the lens of our model, and discuss potential limitations of our model. A more detailed discussion of these issues is provided in the Online Appendix.

Parameter Robustness. In Online Appendix Section C, we investigate the sensitivity of our results to a variety of alternate parameter values. In addition, we implement the procedure of Andrews, Gentzkow, and Shapiro (2017) which highlights which of our empirical targets are important for determining our calibrated parameter values—measured by the magnitude of parameter elasticities to moments. Not surprisingly, the empirical distribution of nominal wage changes is important for pinning down the parameters governing the frequency and cost of on-the-job nominal wage adjustments. The fact that these parameters are pinned down by the distribution of wage changes is of significance because the parameters governing nominal wage stickiness are crucial to both the response of real wages and vacancies to inflationary shocks. If nominal wages within a match were perfectly flexible, real wages and welfare would not fall, and vacancies would not rise in response to a large inflationary shock. Beyond the wage adjustment parameters, Online Appendix C also shows that the search effort-wage elasticity and the average 30-year wage growth moments are important for pinning down the cost elasticity of search (ϕ_s) and the trend in productivity of employed workers (γ_e), respectively. Furthermore, the E-E flows and the U-E flows across the income distribution are important for determining both ϕ_k and ϕ_b, as well as for the parameters governing vacancy costs and home production. Finally, this section shows that the choice of many parameters, such as the elasticity of the search cost function (ϕ_s) or the bargaining weight between workers and firms (τ), has little effect on our key results.

Potential Welfare Gains from Improving Match Quality. A strong assumption we made throughout is that output is only a function of worker productivity. In particular, we have abstracted from both firm-specific and match-specific productivity. Including such forces would not change the underlying mechanism in our model linking rising inflation to declining real wages, increasing worker churn, and rising firm vacancies, given nominal wage rigidities.

However, allowing for match-specific capital could potentially alter our welfare calculations by providing another benefit of inflation to the economy. In related work, Pilossoph, Ryngaert, and Wedewer (2024) develop a model with nominal wage rigidities, frictional labor markets, costly worker search, and match-specific productivity. Within their calibrated model, the increasing churn induced by the recent inflation does increase allocative efficiency in the economy, but the aggregate welfare gains coming from this channel were quantitatively small during this period. The reason for the small effect in their counterfactual is that job-changers were only a small portion of the overall population, and the productivity gains of the marginal movers induced by inflation were relatively modest in magnitude.

Other Labor Market Shocks During the Inflation Period. In Online Appendix Section D, we show how various other labor market shocks—such as an aggregate TFP shock, a discount rate shock, a shock to vacancy posting costs, or a shock to the value of not working—affect labor market outcomes through the lens of our model. We show that none of these other shocks, in isolation, can explain the rise in aggregate vacancies while simultaneously matching the real wage dynamics of job-stayers and job-switchers, as well as other labor market flows. For example, a positive TFP shock can match the large rise in the V/U ratio implied by our baseline model only if real wages also increase substantially, which is counterfactual to the data during this period. Likewise, a large positive demand-side shock (such as a declining discount rate or declining vacancy cost) can match the large rise in the V/U ratio only if there is a corresponding large increase in the U-E rate, and if the wages of both stayers and switchers are relatively constant in the short run. In summary, it is hard for other shocks to generate sharply rising vacancies, while real wages of job-stayers were falling both in absolute levels and relative to those of switchers.

The Underlying Cause of the Inflation and Labor Market Flows. In Online Appendix Section D, we also discuss how the proposed underlying drivers of the recent inflation period would have affected labor market dynamics. Rising oil prices and supply chain backlogs due to pandemic closures have similar effects on the labor market as a negative aggregate productivity shock. These negative supply shocks will reduce labor demand, putting downward pressure on the V/U ratio, E-E flows, U-E flows, vacancies, employment, and average real wage growth. Conversely, a positive aggregate demand shock due to increased government spending, expansive monetary policy, or pent-up demand from the pandemic would increase the demand for labor, putting upward pressure on the V/U ratio, U-E flows, vacancies, employment, and real wages. These two shocks at the center of many explanations for the current inflation have offsetting effects on labor demand. This could be a possible explanation for why aggregate employment (and GDP) did not change much during the current inflation period. If that is the case, the effects of inflation itself could be the primary driver of the real wage dynamics and labor market flows observed during the 2021-2024 period.

Economic Expansions and Declining Wage Inequality. It is well-known that periods of economic expansions are also periods when the bottom of the wage distribution improves relatively more than the top of the wage distribution.[27] Our quantitative framework shows that an inflation shock can also generate a compression in the wage distribution between high and low wage workers. This is also consistent with the data during this period, where the real wage declines were larger for higher wage workers. Autor, Dube, and McGrew (2024) attribute the convergence during this period to the economy being relatively hotter for lower wage workers resulting in increased competition for their labor services. They also show that lower wage workers were systematically moving to better jobs during the inflation period. Our model is a partial equilibrium exercise in which we analyze an increase in the inflation rate, all else being equal. As a result, we cannot rule out that part of the reason lower wage workers had smaller real wage declines, or were moving to systematically better jobs, was due in part to the fact that the aggregate labor demand shock was relatively more positive for lower wage workers. A combination of the nominal wage rigidity framework in our paper, coupled with a higher relative aggregate demand story for lower wage workers, can explain why the real wage declines of lower wage workers were smaller than those of higher wage workers. Such caveats should be kept in mind when interpreting cross-worker wage compression during this period.[28]

6 Inflation and the Vacancy-to-Unemployment Rate Over Time

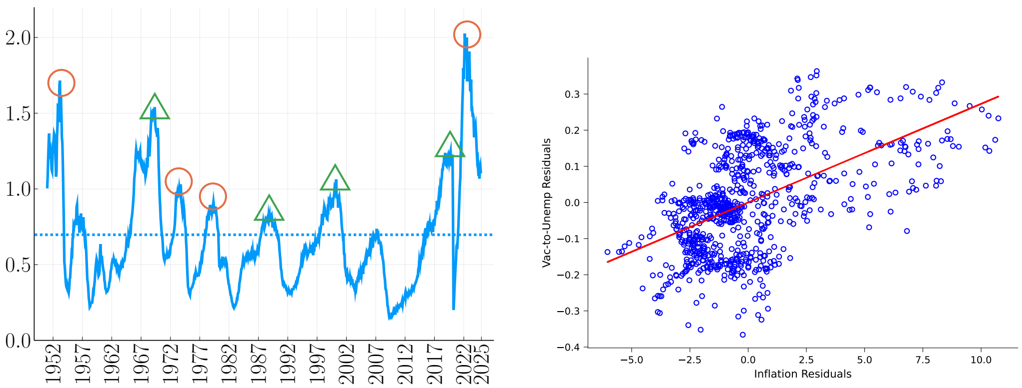
In the final section of the paper, we use historical U.S. data to systematically show that periods of high inflation are associated with an increase in vacancies, an increase in the vacancy-to-unemployment rate, and an upward shift in the Beveridge curve after controlling for the unemployment rate. We show that these periods were also associated with a systematic

[27] See, for example, Okun (1972), Akerlof, Rose, and Yellen (1988), Katz and Krueger (1999), Aaronson et al. (2019), and Autor, Dube, and McGrew (2024).

[28] Jäger et al. (2024) show that lower wage workers systematically underestimate their outside options at other firms. When increasing inflation generates churn, as in our model, it may induce lower wage workers to systematically find better matches relative to higher wage workers, providing an additional reason why inflation generates wage compression.

rise in firm profits, as predicted by our model. These patterns provide evidence that the link between inflation and labor market flows during the post-pandemic period is a broader feature of the U.S. labor market during the last half century.

Figure 6.1: Vacancy to Unemployment Rate and Inflation Over Time



Panel A: V/U Ratio Over Time

Panel B: V/U Residuals vs. Inflation Residuals

Notes: Panel A of Figure shows the evolution of the vacancy to unemployment rate between 1950 and 2024. The periods denoted with a triangle are the periods of high V/U ratio that are consistent with movements along a stable Beveridge curve. The periods denoted with circles are periods of high V/U rate that results from shifts in the Beveridge curve. See text for additional discussion. Panel B formalizes this relationship by plotting residualized monthly V/U ratios against residualized monthly year-over-year inflation rates for the 1950 to 2019 period. The residuals are computed by separately regressing both variables on the unemployment rate and the unemployment rate squared.

Panel A of Figure 6.1 shows the monthly vacancy-to-unemployment rate in the U.S. between 1950 and 2024.[29] As seen from the figure, there are eight periods when the vacancy-to-unemployment rate spiked sharply relative to the average: the early-1950s, the late-1960s, the mid-1970s, the late-1970s, the late-1980s, the late-1990s, the late-2010s, and the post-pandemic period. Four of those periods—where the spikes in the vacancy-to-unemployment rate are denoted with the green triangles—are consistent with the traditional view that a rising vacancy-to-unemployment rate represents a tight labor market; these periods are ones where the economy was moving along a stable Beveridge curve. In particular, the underlying unemployment rate fell sharply as the vacancy-to-unemployment rate rose during each of these periods. These periods were also associated with relatively low and stable inflation rates; the inflation rate during the run up to the green triangle peaks was always less than 4%.

[29]To make this figure, we use data on aggregate U.S. job vacancies produced in Barnichon (2010), who combines data from the Conference Board's Help Wanted Index and Help Wanted Online Index prior to 2000 with the JOLTS dataset after 2000 to make a harmonized monthly vacancy series for the United States.

However, the other four peaks (marked with a red circle) occurred during periods when the inflation rate was rising and at levels that were persistently above 7%. The unemployment rate was either high by historical standards (in the mid- and late-1970s) or relatively constant (during the early 1950s and the 2021-2023 period); these periods, as we show below, are times when the Beveridge curve shifted upwards. Notice that the four periods denoted by the red circles are also periods where it has been shown that aggregate supply shocks were important drivers of the observed inflation.[30]

The above patterns suggest that there may be two proximate causes of a rising vacancy-to-unemployment rate. First, the rising vacancy-to-unemployment rate may be caused by a traditional tight labor market story, such that labor demand (measured by vacancies) exceeded labor supply (measured by the unemployment rate). During these periods, a primitive positive shock to labor demand exerts upward pressure on the vacancy-to-unemployment rate while simultaneously putting downward pressure on the unemployment rate; this is the logic underlying movements along a standard downward-sloping Beveridge curve. However, during other periods, a large burst of inflation may cause excessive labor market churn as workers try to raise their real wages as nominal wages are rigid.[31]

To formally show that high inflation rates are associated with a systematic upward shift in the Beveridge curve, we estimate the following equation using U.S. monthly data between January 1951 and December 2019 (prior to the start of the global pandemic):

$$y_t = \alpha_0 + \alpha_1 \times unemp_t + \alpha_2 \times unemp_t^2 + \beta \times \pi_t + \epsilon_t, \tag{15}$$

where y_t denotes either the vacancy rate or the vacancy-to-unemployment rate in period t depending on the specification. We define $unemp_t$ as the monthly unemployment rate (in percent) and π_t as the monthly year-over-year inflation rate (in percent). To allow for a potential non-linear Beveridge curve, we also include the square of the monthly unemployment rate in some specifications. The relationship between the vacancy rate and the unemployment rate is the traditional Beveridge curve. By including π in the regression, we are assessing whether higher inflation is systematically associated with an upward shift in the Beveridge

[30] The inflationary period from 1950 to 1952 has been attributed to the start of the Korean War, when households scrambled to buy many goods in case there was a return to WWII rationing, and supply was constrained, given the shift of production towards supporting the war (see Reed, 2014). The inflation in the mid-1970s has been linked to rising oil prices.

[31] In fact, Hyatt (2015) shows data on job-to-job flows from 1975 through 2013 using data from the Current Population Survey. He documents that job-to-job flows were at their highest level during this 38-year period period during 1979; this was a time when the inflation rate was approaching its highest level in modern U.S. history.

curve conditional on the unemployment rate.

The results of estimating these regressions are reported in Table 4. Columns (1)-(3) show the results when the dependent variable is the vacancy rate; these regressions explore whether inflation is systematically correlated with shifts in the Beveridge curve. Columns (4)-(6) have the vacancy-to-unemployment rate as the dependent variable. As seen in columns (1) and (4), the unemployment rate itself is a strong predictor of movements in both the vacancy rate and the vacancy-to-unemployment rate. The former is the well-documented Beveridge curve relationship, while the latter finds that market tightness increases when the unemployment rate is low—the traditional tight labor market story.

Columns (2) and (5) highlight the main contribution of our paper. In particular, the results in these columns show that higher inflation is associated both with an upward shift in the Beveridge curve by increasing vacancies conditional on unemployment (column (2)) and an increase in the V/U rate conditional on unemployment (column (5)). For example, the regression shows that an increase in the inflation rate of 10 percentage points is associated with an increase in the vacancy-to-unemployment rate of 0.24. This is a large effect, given that the average vacancy-to-unemployment rate during this period is about 0.7. As a reminder, these regressions are estimated using data prior to 2020, suggesting that the link between inflation and vacancies is a common feature of U.S. labor markets during the last 75 years. Finally, columns (3) and (6) show that the inflation results persist even when we allow for a non-linear Beveridge curve by including the square of the unemployment rate in the regression.

Table 4: Historical Beveridge curve Estimation

	Vacancy Rate			Vacancy-Unemp Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp. Rate (%)	-0.261	-0.301	-0.545	-0.154	-0.160	-0.542
	(0.015)	(0.013)	(0.076)	(0.004)	(0.003)	(0.015)
Unemp. Rate Sq.			0.019			0.030
			(0.006)			(0.001)
Inflation Rate (%)		0.149	0.151		0.024	0.027
		(0.007)	(0.007)		(0.002)	(0.001)
R^2	0.26	0.50	0.51	0.68	0.73	0.85

Notes: The table shows the coefficients from the estimation of equation (15). Each observation is a month between January 1951 and December 2019. Robust standard errors are in parenthesis.

Panel B of Figure 6.1 plots the partial effect of inflation on the vacancy-to-unemployment rate during the 1950-2019 period in graphical form. In particular, we regress the monthly inflation rate on the monthly unemployment rate and the unemployment rate squared and take the residuals from this regression; we denote this as the residualized inflation rate. We then repeat these steps for the vacancy-to-unemployment rate and plot the two residuals against each other. The slope of the line through the scatter plot is the same as the inflation regression coefficient in column (6) of Table 4. The benefit of the figure is to show that the inflation coefficients in the above table are not being driven by outliers. It is worth noting that the points in the upper-right quadrant of this figure all originate from months either during the 1970s or the early 1950s.

Lastly, consistent with our sticky wage model, the corporate profit-to-GDP ratio also systematically increases during inflationary periods. 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. Additionally, in mid-2022, the corporate profit to GDP ratio was at 12%, which was the highest level during the prior 75 years. In Appendix Table B.5 and Appendix Figure B.15 of the online appendix, we show that the corporate profit to GDP ratio systematically increases during periods of inflation conditional on the unemployment rate, and, relatedly, there is a strong positive relationship between the residualized corporate profit share and the residualized inflation rate in U.S. data over the last 75 years.

7 Conclusion

The dramatic recent increase in the vacancy-to-unemployment rate has renewed interest among both academics and policymakers about the causal effect of tight labor markets on inflation. In this paper, we develop a model that combines elements of modern frictional labor markets with nominal wage rigidities to show that the causation can flow in the opposite direction: High unexpected inflation can drive a rise in the vacancy-to-unemployment rate, creating the appearance of a tight labor market even as real wages fall. Calibrating the model with pre-2020 data, we show that our model successfully matches trends in worker flows and wage changes during the 2021-2024 period, where the only underlying shock is a rise in inflation. We provide additional evidence of our model mechanisms using historical data. In particular, prior periods of high inflation within the United States were systematically associated with increases in vacancies, an upward shift in the Beveridge curve, and rising firm profits.

We also use the calibrated model to compute the welfare losses to U.S. workers generated by the recent inflation. The model implies that the median worker cumulatively lost approximately one-fifth of one month's consumption stemming from the 2021-2023 inflation, equivalent to about $1000 for the median worker. Most of the welfare loss stems from the real wage declines, given that nominal wages are sticky, which effectively transfers resources from workers to firms. Our framework, therefore, also provides a rationale for the historically high profit rate of U.S. firms during the recent inflation period. However, we also identify additional real costs and benefits from the recent inflation above and beyond the transfer between workers and firms: Workers are made worse off by the additional search and renegotiation costs incurred to escape the nominal wage rigidity but benefit from inflation-induced reductions in layoffs.

The goal of our paper is not to explain the causes of the recent inflation but rather to assess how inflation itself can causally affect labor market dynamics. Nevertheless, the underlying causes of 2021-2023 inflation have their own direct effects on the labor market. Negative aggregate supply shocks due to pandemic-induced supply chain bottlenecks will increase prices but reduce labor demand, firm vacancies, and real wages. Conversely, positive aggregate demand shocks due to increased government spending and deferred consumption from the pandemic will also increase prices but increase labor demand, firm vacancies, and real wages. While both of these broad shocks have been identified as important drivers of the recent inflation, they have offsetting effects on the labor market. It would be fruitful for future work to develop a model that incorporates how both of the underlying causes of inflation directly affect labor outcomes, alongside our innovation of incorporating the direct effect of inflation on the labor market highlighted in this paper. Additionally, to fully account for the labor market dynamics during this period, it would be desirable to account for the recent amenity of being allowed to work from home as in Bagga et al. (2025). Their framework can explain why the real wages of high productivity workers—who are more likely to work from home—remain significantly depressed relative to trend even by late 2024, a phenomenon our model cannot explain. Ultimately, all of these forces—the direct effect of inflation on the labor market, the effect of the shocks that caused the inflation, and the effects stemming from the innovation in working from home—jointly determined labor market flows and wages during this period.

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Online Appendix

“A Theory of How Workers Keep Up With Inflation”

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Abstract: We develop a model that integrates modern theories of labor market flows with nominal wage rigidities to study the consequences of inflation on the labor market. Nominal wage stickiness incentivizes workers to engage in job-to-job transitions after an unexpected increase in the price level. Such dynamics lead to a rise in aggregate vacancies associating a seemingly *tight* labor market with *lower* real wages—two facts observed during the recent inflation period. The calibrated model jointly matches aggregate and cross-sectional trends in worker flows and wages during the 2021-2024 period. Using historical data, we show that prior periods of high inflation were also associated with increasing vacancies and upward shifts in the Beveridge curve. Our results suggest that policymakers and academics should be cautious about viewing the rise in the vacancy-to-unemployment rate as a sign of a tight labor market during inflationary periods without holistically looking at other labor market indicators.

Table of Contents for the Online Appendix

A Data Description

In this section of the appendix, we discuss in detail the data we use in Section 2 of the paper. Some of these data will also be used to calibrate our model. We discuss our calibration procedure separately below.

A.1. JOLTS

We use the Job Openings and Labor Turnover Survey (JOLTS) data to measure quits, layoffs, and vacancies during the period from January 2016 through December 2024. We downloaded the data directly from the JOLTS data website.[1] 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 monthly employment. 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).

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 monthly employment and vacancies. This data was also used when making the vacancy-to-unemployment rate series shown in Panel A of Figure 1.1.

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*.[2] 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

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

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

sample for eight months and then re-enter for a final four additional months. In their fourth survey month and their eighth 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 workers paid hourly, their hourly wage is their self-reported per-hour wage. For salaried workers, the hourly wage is computed as weekly earnings divided by usual weekly hours worked. The Atlanta Fed provides data on the nominal wage growth of the median worker, as well as nominal wage growth for all four quartiles of the wage distribution. They also provide nominal wage growth separately for job-stayers and job-changers.

We use nominal wage growth data to construct real wage indices. Let g_t^{YoY} be the year-over-year nominal wage growth provided by the Atlanta Fed. Then, we map g_t^{YoY} to month-over-month nominal wage growth $g_t^{MoM} = (1 + g_t^{YoY})^{1/12} \approx 1 + \frac{g_t^{YoY}}{12}$. Then, the nominal wage index is given by $\text{Nominal Wage Index}_{t+1} = \text{Nominal Wage Index}_t \times g_t^{MoM}$, normalizing December 2015 to 1. We then take the Consumer Price Index from https://fred.stlouisfed.org/series/CPIAUCSL to construct a price index in the exact same way we constructed the nominal wage index. Finally, we divide the nominal wage index by the price index to generate a real wage index. Given our real wage index, we estimate the pre-period trend in real wages with the following equation $\text{Real Wage Index}_t = \beta_0 + \beta_1 t + \epsilon_t$ on the pre-period $2016 - 2019$ where t represents months since December 2015. We use estimates of β_0 and β_1 to construct a predicted real wage index (trend lines). Given nominal wage growth data workers at different parts of the wage distribution and industries, we use the same procedure described above to construct group-specific trends.

A.3. Aggregate Worker Flows

We use aggregate data from the *Current Population Survey (CPS)* to plot the aggregate trends in worker flows between employers (E-E flows), between unemployment and employment (U-E flows), and between employment and unemployment (E-U flows).

Employment and Unemployment Rates: We downloaded the employment-to-population ratio for individuals aged 15-64 and the overall unemployment rate directly from the St. Louis Federal Reserve's Economic Database (FRED) which extracted the series from *Current Population Survey*. We downloaded the series "Infra-Annual Labor Statistics: Employment Rate Total: From 15 to 64 Years for United States" and "Unemployment Rate" at https://fred.stlouisfed.org/series/LREM64TTUSM156S and https://fred.stlouisfed.org/series/UNRATE, respectively.

E-E Flows: When measuring aggregate E-E flows, as shown in Panel A of Figure 2.2, we use the data series created by Fujita, Moscarini, and Postel-Vinay (2024). The Fujita, Moscarini, and Postel-Vinay (2024) series uses data from the *Current Population Survey* to make a measure of aggregate E-E flows that is consistently measured over time. We downloaded the data directly from https://www.philadelphiafed.org/surveys-and-data/macroeconomic-data/employer-to-employer-transition-probability. The Philadelphia Federal Reserve updates the data series every month. We take a three-month moving average when plotting the data.

U-E Flows: To create an aggregate measure of U-E flows, we downloaded the series "labor force flows unemployed to employed" and "unemployment level" from the St. Louis Federal Reserve's Economic Database (FRED), which extracted the series from *the Current Population Survey* aggregates published by the BLS to calculate the U-E rate; both are provided at the monthly level. We divide the former by the latter and then take a three month moving average to calculate the monthly U-E rate. The two series can be found at https://fred.stlouisfed.org/series/LNS17100000 and https://fred.stlouisfed.org/series/UNEMPLOY, respectively.

E-U Flows: To create an aggregate measure of E-U flows, we downloaded the series "labor force flows employed to unemployed" and "all employees, total nonfarm" directly from the St. Louis Federal Reserve's Economic Database (FRED), which extracted the former series from *Current Population Survey* aggregates (published by the BLS) and the latter series from *Current Employment Survey* aggregates (also published by the BLS) to calculate the E-U rate. We divide the former by the latter and then take a three-month moving average to calculate the monthly E-U rate. The two series can be found at https://fred.stlouisfed.org/series/LNS17400000 and https://fred.stlouisfed.org/series/PAYEMS, respectively.

A.4. ADP Pay Insights

The ADP Pay Insights Data uses data from the universe of payroll checks processed by ADP to measure nominal earnings changes for the median U.S. worker (year-over-year) as well as for various demographic groups, industries, and firm size groups. They also measure nominal earnings growth separately for job-stayers and job-changers. For a full discussion of the ADP data and its representativeness for the U.S. economy, see Grigsby, Hurst, and Yildirmaz (2021). We downloaded the data directly from https://payinsights.adp.com/.

A.5. Longitudinal Employer-Household Dynamics (LEHD)

The LEHD provides the level of employment and the level of employer to employer flows (with no observed unemployment spell) by education groups. We use this data to construct E-E rates by education groups—specifically for high school graduates and college graduates. This data is publicly available and can be downloaded here https://ledextract.ces.census.gov/.

A.6. Data Construction for Calibration

We use the Outgoing Rotation Group (ORG) of the Current Population Survey (CPS) and the Annual Social and Economic Supplement (ASEC) to estimate worker flows such as employment-unemployment (E-U), unemployment-employment (U-E), and employment-employment (E-E) rates conditional on a worker's position in the earnings distribution.

We download the March ASEC from IPUMS for the years $2016 - 2019$. We use the variable INCWAGE which indicates each respondent's total nominal pre-tax wage and salary income–that is, money received as an employee–for the previous calendar year to recover a worker's position in the earnings distribution. We drop all individuals who report 0 earnings and restrict the sample to full-year, full-time workers defined as those who reported working more than 40 weeks (WKSWORK1) and 35 hours each week (UHRSWORKLY). We construct a measure of weekly earnings by dividing INCWAGE by WKSWORK1 and an hourly wage by dividing weekly earnings by hours worked in a usual week. We filter out the top and bottom 1% of weekly earnings within each year from our sample. We use the Consumer Price Index to convert reported nominal earnings into real terms. Given real earnings, we classify workers into earnings deciles within each year. In addition, we compute the cross-sectional weekly earnings distribution, which is used to calibrate the model.

A.6.1. Labor Market Flows. We use the CPS basic monthly files to estimate worker 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 worker flows from employment to unemployment (E-U) and from unemployment to employment (U-E). In addition, we also observe a change in employers across adjacent months, which allows us to measure employer to employer (E-E) flows. There are several technical issues that warrant discussion here. Fujita, Moscarini, and Postel-Vinay (2024) show that the CPS systematically underestimates E-E flows since 2007 due to changes in survey methodology, which induce selection on both unobservable and observable worker characteristics that are correlated with E-E transitions. We use their published aggregate E-E series to discipline our E-E rates by earnings deciles. Our raw E-E estimates by various groups underestimate the true E-E flows, so we use a constant scaling factor to scale our E-E flows by deciles to match the aggregate E-E rate as calculated by Fujita, Moscarini, and Postel-Vinay (2024). The decision to use 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 our model, returns to search effort, in expectation, are decreasing in current earnings. Therefore, search effort, and in turn, E-E rates are more elastic at the bottom of the earnings distribution, which implies that a constant scaling factor underestimates the true E-E rate for low earners and overestimates E-E rates for high earners. Thus, our estimates, which show that E-E rates increased more for low earners relative to high earners, represent a conservative lower bound. Similarly, we scale our E-U and U-E estimates to fit the aggregate E-U and U-E estimates provided by FRED. We use the following equation to determine our scaling factor:

$$X = \frac{\alpha}{10} \sum_{d=1}^{10} X_d \tag{A.1}$$

where X represents the aggregate moment published by FRED (E-U, U-E, E-E) and X_d represents our decile-specific estimates from the micro-data.

A.6.2. Classifying E-U flows. Workers flow into unemployment for many different reasons. The CPS variable WHYUNEMP provides 6 different reasons for worker's unemployment status. The reasons are (1) Job Loser/on layoff, (2) other job loser, (3) temporary job ended, (4) job leaver, (5) Re-Entrant, (6) New-Entrant. In the paper, E-U flows are characterized by an endogenous component—related to optimizing worker and firm choices—and an exogenous component. The 2 endogenous components underlying E-U flows are layoffs (1) and quits (4). The flows that cannot be explained by these two forces are exogenous $(2, 3)$. We do not use extensive margin flows characterized by $(5, 6)$ as these are not E-U flows. We apply the same α_{E-U} scaling factor for the endogenous and exogenous components so that we fit the aggregate E-U rate.

A.7. Work from Home Measures

We use the Dingel and Neiman (2020) measures to determine which occupations have work from home potential when exploring whether real wages have evolved differentially across occupations. Dingel and Neiman (2020) assess the feasibility of working from home across occupations using survey-based data from O*NET. They validate their classification algorithm by comparing its output to manually assigned indicators. The work-from-home classification for each occupation, mapped to the Occupational Employment and Wage Statistics (OES) from the U.S. Bureau of Labor Statistics, is available at: https://github.com/jdingel/DingelNeiman-workathome/tree/master/onet_to_BLS_crosswalk/output. The codes provided by Dingel and Neiman (2020) map directly into the CPS's occupation codes.

We improved the matching between the occupation codes from the Atlanta Fed data and Dingel and Neiman (2020) for two reasons. First, roughly 12% of the Atlanta Fed observations contain four-digit occupation codes that are not used in Dingel and Neiman (2020). Second, the Atlanta Fed data include less granular occupation codes that do not map directly to Dingel and Neiman (2020) classifications. To reconcile these discrepancies, we proceed as follows. For each unmatched higher-level occupation code in the Atlanta Fed data, we first identify its corresponding subcategories in the Dingel and Neiman (2020) data based on the leading digits. If all subcategories share the same telework classification, we randomly select one of the subcategory occupation codes from Dingel and Neiman (2020) and use it to replace the higher-level code in the Atlanta Fed data. If the subcategories differ in their telework classification, we determine the appropriate telework indicator for the higher-level code and then randomly select a subcategory with the same telework classification for replacement.

As an illustrative example, the occupation code "Software developers, applications and systems software (15-113X)" in the Atlanta Fed data can be matched with four more specific occupation codes in Dingel and Neiman (2020): Computer Programmers (15-1131), Software Developers (15-1132, 15-1133), and Web Developers (15-1134). Since all of them are indicated as teleworkable jobs, we recode the Atlanta Fed data from 15-113X to 15-1131. Before the manual fix, 55.8% of the observations in the Atlanta Fed data matched the Dingel and Neiman (2020) classification. The merge rate increased to 86.9% after the manual fix.

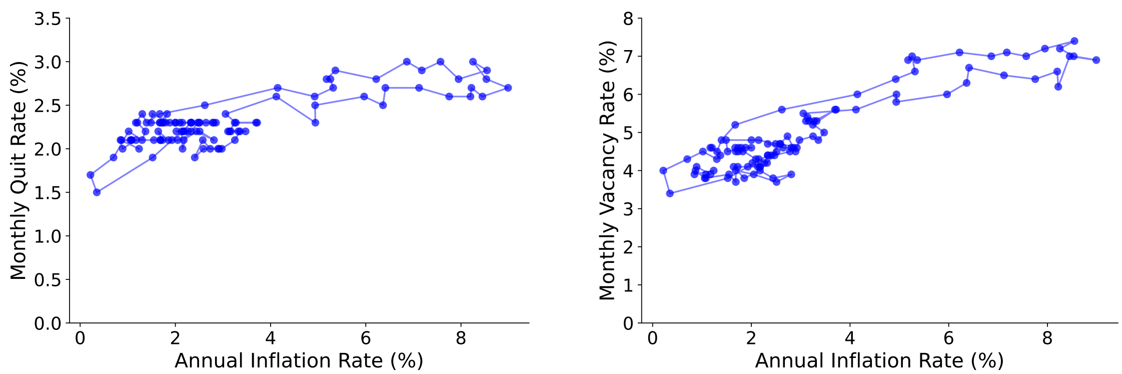
B Additional Descriptive Results

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

B.1. Annual Inflation vs Monthly Quits and Vacancies

In this subsection, we show the tight relationship between monthly quits and vacancies with the monthly year-over-year inflation rate during the 2016-2024 period. As seen from Panel A of Appendix Figure B.1, 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 0.104 percentage point increase in the quit rate (standard error = 0.007); the R-squared of the regression was 0.66.

Figure B.1: Annual 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.

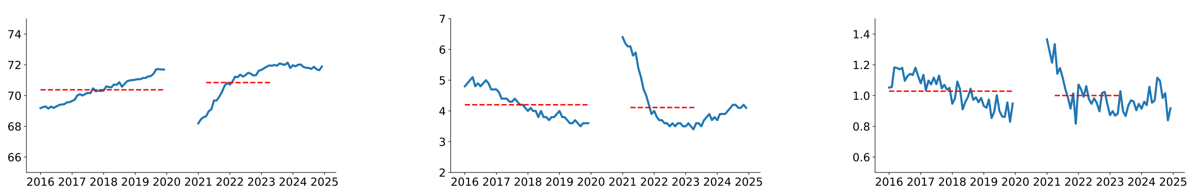
Likewise, as seen from Panel B of Appendix Figure B.1, there is also a tight relationship between the year-over-year CPI inflation rate and the monthly vacancy rate. This figure is analogous to the Beveridge curve, but with the price inflation rate on the x-axis instead of the unemployment rate. While 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 0.439 percentage point increase in the vacancy rate (standard error = 0.019); the R-squared of the regression was 0.83.

B.2. Dynamics of Employment and Unemployment During the Inflation Period

In this section, we show the dynamics of the U.S. employment to population ratio for 15 to 64 year olds and the U.S. unemployment rate during the 2016-2024 period. We also show aggregate trends in the E-U rate as well as a decomposition of the unemployment rate dynamics into changes in the job destruction rate versus changes in the job finding rate.

Panels A through C of Figure B.2 show the employment to population ratio for 16-65 year olds, the aggregate unemployment rate, and the aggregate E-U rate from January 2016 through December 2024. As with the figures in the main text, the two red lines represent the average of each series between the pre-period (January 2016 through December 2019) and the inflation period (April 2021 through May 2023). The average employment to population ratio was 70.4 and 70.8, respectively, during the pre-period and inflation period; there was not much change in aggregate employment rates between the pre-period vs the inflation period. Likewise, the average unemployment rates were 4.2 and 4.1, respectively, during the pre-period and inflation period. Finally, the E-U rate did not change at all during the inflation period relative to the pre-period. This finding implies that all of the documented quits from the JOLTS data are showing up as increased E-E churn, as opposed to systematic quits to unemployment. All three series show that the economy recovered to roughly pre-pandemic levels by the fall of 2021, highlighting that aggregate labor market conditions were roughly comparable between the pre-period and the inflation period.

Figure B.2: Employment-to-Population, Unemployment Rate and E-U Flows

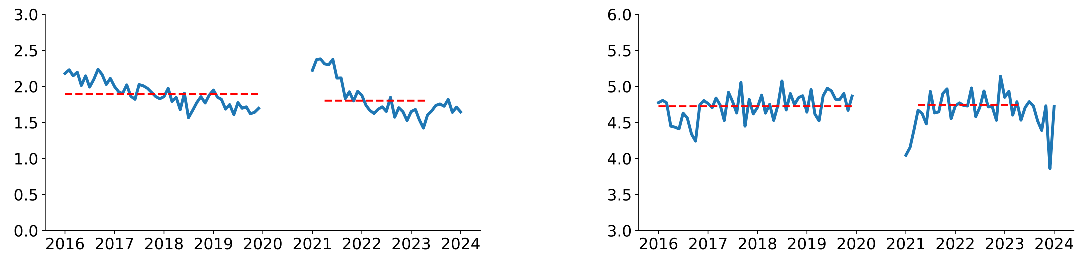


Panel A: EPOP | Panel B: Unemployment Rate | Panel C: E-U Rate

Notes: Figure shows the monthly employment-to-population ratio for 15–64 year olds (Panel A), the unemployment rate (Panel B), and the E-U rate (Panel C) during the 2016–2024 period in the United States. Data is from the St. Louis Federal Reserve Economic Database (FRED). For readability, we exclude the data from 2020 which featured several months of double digit unemployment, sharply declining employment-to-population ratios, and very high levels for the E-U rate during the initial months of the pandemic.

Appendix Figure B.3 shows the time series of the aggregate flows out of the labor force into unemployment (NU rate) and the aggregate flows out of the labor into employment (NE rate) from the St. Louis Federal Reserve's Economic Database (FRED). On average, the NU rate and the NE rate were nearly identical between the pre-period and the inflation period. As with the aggregate employment to population ratio, unemployment rate, and E-U rate, any effects of the pandemic on these flows were over by the fall of 2021.

Figure B.3: Extensive Margin Labor Market Flows



Panel A: NU Rate Panel B: NE Rate

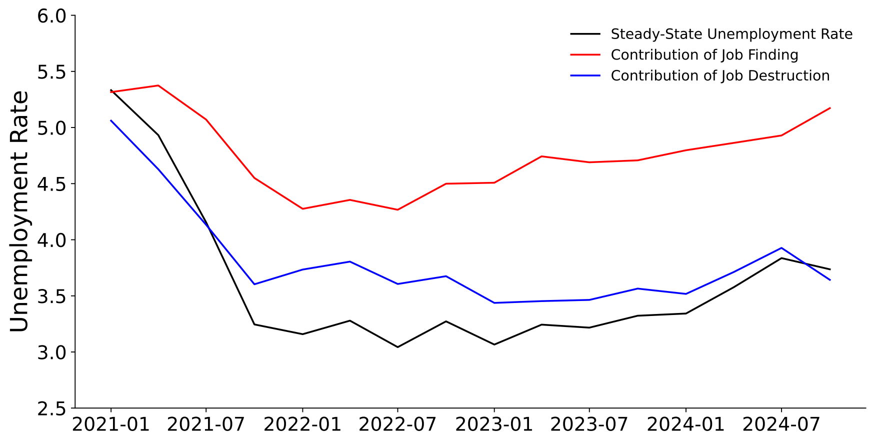
Notes: The figures show labor market flows from non-participation (N) to unemployment (U) and employment (E). Each figure shows pre-period and inflation period averages. Data is from the St. Louis Federal Reserve Economic Database (FRED). For readability, we exclude the data from 2020

Appendix Figure B.4 shows that the decline of unemployment between January 2021 and September 2021 coming out of the pandemic (black line) was largely driven by the declining job destruction rate (or layoffs, blue line) rather than the increasing job finding rate (red line). The fluctuations in the job-finding rate (red line) predict persistently higher unemployment than what was observed during this period. Instead, the changes in the 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.[3] 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 was driving unemployment dynamics.

Finally, Table B.1 explores whether the employment-to-population ratio changed meaningfully for different demographic groups between the pre-period (column 1) and various time periods during the post-pandemic period (columns 2-5). In particular, we examine whether the demographic condition changed during the inflation period (2021M4-2023M5) similar

[3]We thank Joe Hazell for suggesting that we add this decomposition to the appendix.

Figure B.4: Decomposition of Unemployment Dynamics



Notes: Contribution of fluctuations in the job finding (U-E) and job destruction (E-U) 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 $1990-2024$.

to the aggregate results shown above (column 2). As seen from the table, the employment rate was essentially unchanged between the periods for the four demographic groups.[4] We also explored the employment rate for different demographic groups during the inflation period and post-inflation period (2021M4-2024M12, column 3), the early part of the inflation period (2021M4-2021M12, column 4), and the 2022M1-2024M12 period (column 5). Again, the employment rates for the different demographic groups were roughly similar across all of these time periods. Collectively, these results suggest that there were not large demographic shifts during the pre-period and the inflation period that could contaminate the aggregate flows we highlight in the main paper.

B.3. Job-Stayers vs Job-Changer Wage Growth, Atlanta Fed

In the main text, we used *ADP* data to measure the nominal earnings growth of job-stayers vs job-changers. In this subsection, we show similar patterns from the *Atlanta Fed Wage Tracker Index*. The *Atlanta Fed Wage Tracker Index* also measures the nominal wage growth of job-stayers relative to job-changers over time. However, researchers should be cautious when using the CPS data—which underlies the Atlanta Fed Wage Tracker Index—when comparing the wage changes of job-changers to those of job-stayers. The reason is that the

[4] Women with a bachelor's degree experienced a slight increase in their employment rate over this time period, but this is a continuation of a trend that pre-dated 2020.

Table B.1: Employment to Population Ratio Over Time, 15-64 Year Olds

Education	2016M1–2019M12	2021M4–2023M5	2021M4–2024M12	2021M4–2021M12	2022M1–2024M12
Men: Less than Bachelors	0.686	0.681	0.684	0.672	0.687
Men: Bachelors or More	0.885	0.883	0.884	0.876	0.886
Women: Less than Bachelors	0.574	0.569	0.575	0.558	0.579
Women: Bachelors or More	0.786	0.794	0.798	0.783	0.802
All	0.692	0.697	0.701	0.686	0.705

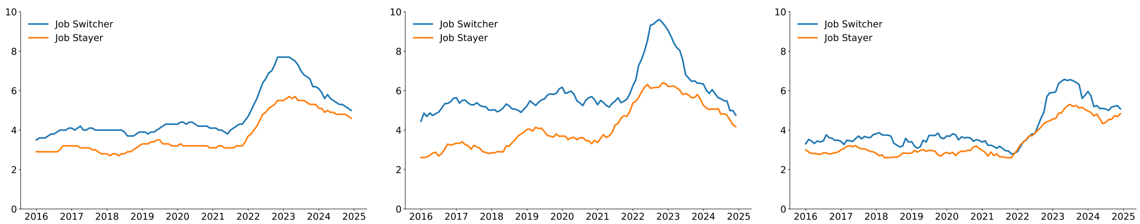
Notes: The first four rows of the table show the average employment rate for men and women with less than a Bachelor's degree and men and women with a Bachelor's degree or more in different time periods. The last row shows the average employment rate pooling men and women of all education levels. Each columns shows is associated with a time period. The sample focuses on those aged 15-65 from the monthly CPS files.

job-changer measure in the CPS data is measured with substantial error when comparing individual observations one year apart. As we show here, the qualitative patterns between wage-changers and wage-stayers in the Atlanta Fed are similar to those found in the ADP data. However, the quantitative magnitudes of the gaps are muted, consistent with measurement error in the job-changer measure.

There are two key limitations to using the *CPS* data to measure the wage growth of job-changers over a 12 month period. Both of these limitations result in the gap between the wages of job-stayers and job-changers being biased downward in the CPS data relative to other datasets like ADP. First, individual job-changing statuses need to be imputed to match their corresponding wage data. As discussed above, the CPS measures an individual's wage in their outgoing rotation data (waves 4 and 6 of an individual's time in the CPS). These outgoing rotations are 1 year apart. However, the individual only has actual information on whether they changed employers in waves 2, 3, 4, 6, 7, and 8. In these waves, individuals are explicitly asked whether they changed employers relative to the previous month. There is a 9 month gap between wave 4 and wave 6 during which there is no information on whether the CPS individual changed jobs. As has been done by others in the literature (e.g., Autor, Dube, and McGrew (2024)), the Atlanta Fed imputes whether the individual changed jobs if either their occupation or industry changed between waves 4 and 6. This induces two types of measurement error. First, some job-changers will be included in the job-stayer sample if they changed jobs but remained in the same occupation or industry. Second, some job-stayers will be included in the job-changer sample if their occupation or industry was misreported. It has been found that there is a large amount of measurement error in the CPS occupation and industry codes (e.g., Kambourov and Manovskii (2013)). These two types of measurement error will narrow the gap in the wage change between job-stayers and job-changers.

The second type of measurement error for job-changers in the CPS data is that the CPS follows addresses, not people. If someone moves addresses, they drop out of the *CPS* sample. Job-changers—particularly those who receive large wage increases—are more likely to move locations than job-stayers. Thus, 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.

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



Panel A: All Workers | Panel B: Quartile 1 | Panel C: Quartile 4

Notes: Figure shows nominal wage growth of job-stayers (yellow bottom line) and job-changers (blue top line) from the Atlanta Fed's Wage Tracker Index. Panel A shows the patterns for all workers in the Atlanta Fed data. Panels B and C show the patterns for workers in the bottom and top quartiles of the wage distribution, respectively. See text for additional details of the data. For Panel A, we downloaded the data for this figure directly from the Atlanta Fed's Wage Tracker website. For Panels B and C, we used the Atlanta Fed's processed micro data to compute the patterns for different income groups.

Despite the large measurement error in job-changing status within the CPS, the patterns in the Atlanta Fed data are broadly similar to what we show in the main paper using ADP data.[5] Appendix Figure B.5 shows the annual nominal wage growth for job-stayers (bottom yellow line) and job-changers (top blue line) for all workers (Panel A), workers in the bottom income quartile (Panel B), and workers in the top income quartile (Panel C). The gap in wage growth between job-changers and job-stayers widened for all groups during the inflation period. As with the ADP data, the gap between the wage growth of job-changers and job-stayers grew as the inflation rate increased. However, relative to the ADP data, the gap between 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 CPS job-changers are measured with considerable error.

[5]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 earnings series for job-stayers and job-changers.

Keeping the measurement error in mind, Table B.2 explores whether there are demographic composition shifts between job-stayers and job-changers when comparing the pre-period and the inflation period. In particular, this table helps to explore whether composition shifts can explain the widening gap in the wage growth of job-stayers versus job-changers during the inflation period. The table uses the Atlanta Fed microdata on which their Wage Tracker is based. We then compute the demographic composition of job-stayers and job-changers in the pre-period (2016-2019). These results are shown in columns (1) and (2). We then compute the demographic composition of both groups during the inflation period (2021M4-2023M5). These results are shown in columns (3) and (4). As seen from the table, the relative demographic composition between job-stayers and job-changers is mostly the same during the inflation period with respect to gender, race, and age. As predicted by our model, job-changers are slightly less educated and come from lower income groups during the inflation period. These differences are quantitatively small.

Table B.2: Selection Table

	Pre-Period		Inflation Period		Difference		p-value of Diff-Diff
	Job Stayer	Job Changer	Job Stayer	Job Changer	(2)-(1)	(4)-(3)	(5)-(6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share Bachelors+	0.42	0.36	0.46	0.38	-0.06	-0.08	0.00
Share Male	0.49	0.53	0.49	0.54	0.04	0.05	0.42
Share Non-White	0.17	0.18	0.18	0.19	0.01	0.01	0.40
Share 1st Wage Quartile	0.23	0.28	0.22	0.28	0.05	0.06	0.07
Share 2nd Wage Quartile	0.24	0.26	0.23	0.27	0.02	0.03	0.09
Share 3rd Wage Quartile	0.26	0.23	0.27	0.23	-0.02	-0.03	0.22
Share 4th Wage Quartile	0.27	0.23	0.28	0.22	-0.04	-0.06	0.02
Mean Age	45.03	42.86	45.23	42.84	-2.17	-2.39	0.25

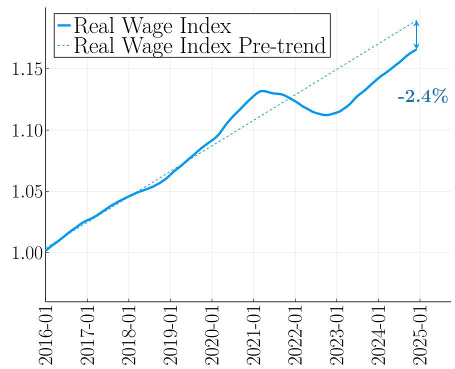
Notes: Table shows the demographic composition of job-stayers and job-changers during the pre-period (2016M1-2019M12) and the inflation period (2021M4-2023M5) using the processed microdata underlying the Atlanta Fed Wage Tracker Index. Column (5) shows the difference between job-stayers and job-changers during the pre-period. Column (6) shows the difference between the two groups during the inflation period. Column (7) shows the p-value of the difference between columns (5) and (6).

B.4. Additional Wages Dynamics During the Inflation Period

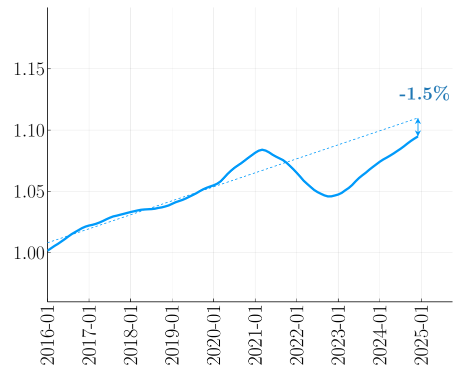
In this subsection, we present additional data on real wage growth throughout the wage distribution during the inflation period, as well as real wage growth across education groups. To start, Appendix Figure B.6 shows the real wage growth for quartiles 1, 2, 3, and 4 during the 2016-2024 period. Panels B and C of Figure 2.4 of the main text show the real wage growth of quartiles 1 and 4 relative to their predicted trend by WFH status. This appendix figure shows the underlying data on which the figure in the main text is based, without separating it by WFH status. We also show the raw real wage series for quartiles 2 and 3.

The panels in this figure give readers a sense of the overall pre-trends in real wages during the 2016-2019 period for each of the income quartiles.

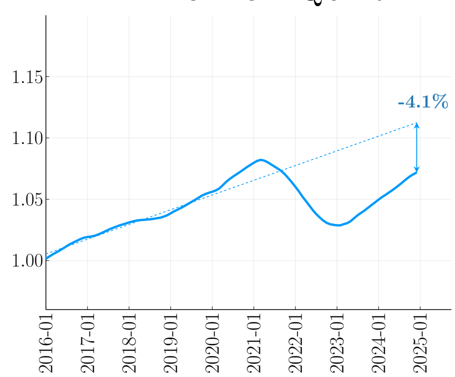
Figure B.6: Real Wage Growth, By Wage Quartile



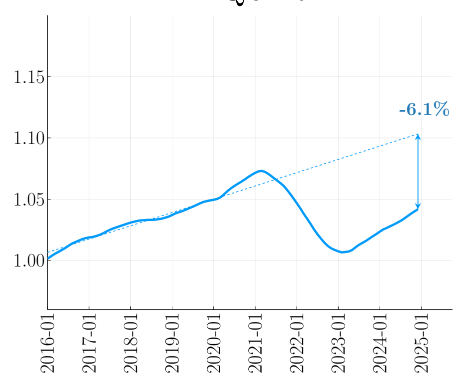
Panel A: Bottom Quartile



Panel B: Quartile 2



Panel C: Quartile 3

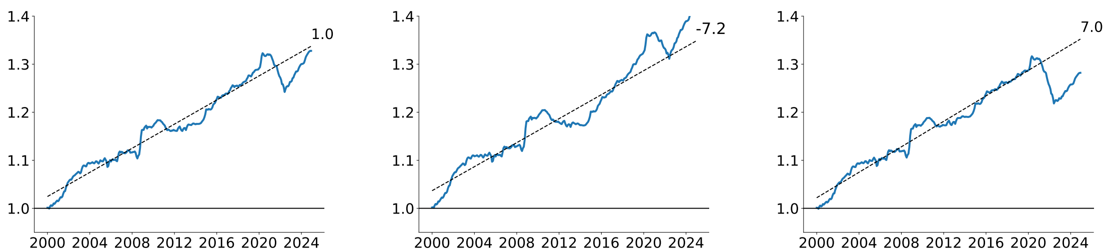


Panel D: Top Quartile

Notes: The figure shows the evolution of real wages from the Atlanta Fed Wage Tracker Index for workers in different income quartiles. Each figure also shows the quartile specific pre-trend in the real wage based on the 2016-2019 data (in the dashed line). We convert the nominal Atlanta Fed Wage Index into a real wage index by deflating the series for each income quartile by the aggregate CPI.

Next, we show that the real wage dynamics during the inflation period shown in Figures 1.1 and 2.4 of the main text 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. Appendix Figure B.7 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 three panels in Appendix Figure B.7; we show the patterns for the median worker (Panel A), bottom quartile workers (Panel B), and top quartile workers (Panel C). The deviation from trend with this alternate method are very similar to what we show in the main text when we compute the pre-trend using the shorter time period. As of December 2024, the median worker still has real wages slightly below trend, while top quartile workers have real wages substantially below trend. The bottom income quartile, however, is now above their expected wage as of December 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. As seen from panel B, using the longer trend implies that real wages were also substantially above trend during the 2016-2019 period.

Figure B.7: Evolution of Real Wages with Alternative Pre-Trend

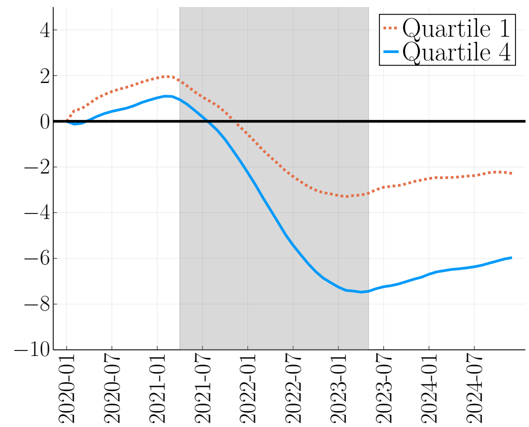


Panel A: All Workers | Panel B: Bottom Quartile | Panel C: Top Quartile

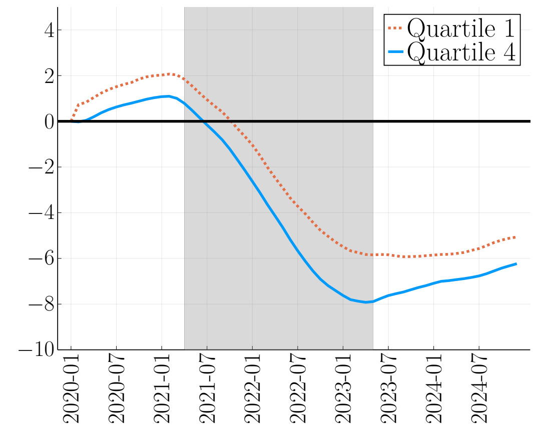
Notes: This figure shows the evolution of median real wages between 2000 and 2024 for a sample of all workers (Panel A), bottom quartile workers (Panel B), and top quartile workers (Panel C). The blue line indicates the real wage series while the dotted black line shows the predicted trend in real wage based on $2000 - 2019$ data. We compute the predicted trend separately for each of the three panels. The underlying data comes from from the Atlanta Fed Wage Tracker website.

Appendix Figure B.8 shows the real wage growth relative to the predicted trend for workers with less than a bachelor's degree (Panels A and C) and for workers with a bachelor's degree or more (Panels B and D). Panels A and B of the figure show the real wage patterns for workers in the top and bottom quartiles of the aggregate wage distribution within that education group. As a result, the cutoffs for being in the top and bottom wage quartiles are similar across the two panels. Panels C and D of the figure show the real wage patterns for workers in the top and bottom quartiles of their education specific wage distribution within that education group. As a result, the cutoffs for being in the top and bottom wage quartiles differ between the two panels. For all panels, we compute the real wage pre-trends using data from 2016 to 2019 and allow the pre-trends to differ for each education and income quartile group. The data come from the processed CPS microdata produced by the Atlanta Fed to create their Wage Tracker Index. This appendix figure shows that our key patterns regarding real wage declines being larger for high income workers also hold *within* education groups. For both low and high educated workers, real wages fell more relative to trend for higher

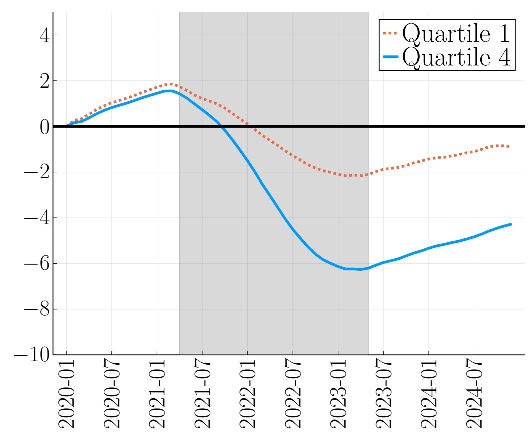
Figure B.8: % Deviations from Trend in Real Wages by Education



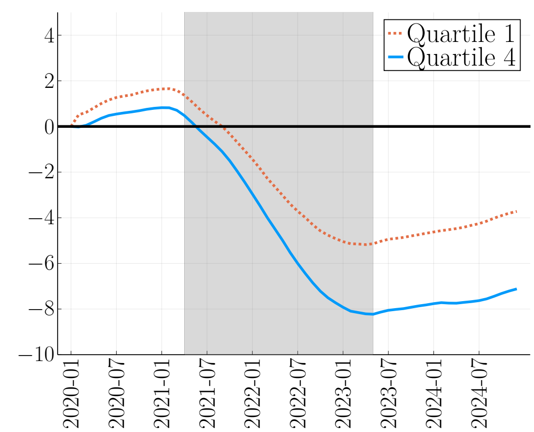
Panel A: Education < 16
(Aggregate Quartiles)



Panel B: Education ≥ 16
(Aggregate Quartiles)



Panel C: Education < 16
(Within-Education Quartiles)



Panel D: Education ≥ 16
(Within-Education Quartiles)

Notes: Figure shows the real wage growth relative to predicted trend for workers with less than bachelor's degree (Panels A and C) and workers with a bachelor's degree or more (Panels B and D). Panels A and B show the real wage patterns for workers in the top and bottom quartiles of the aggregate wage distribution within that education group. We compute the quantiles based on the aggregate distribution so they are defined similarly for both education groups. Panels C and D show the real wage patterns for workers in the top and bottom quartiles computed separately within each education group's own wage distribution. See text for additional details.

wage workers relative to lower wage workers. These patterns hold regardless of whether we define high and low wage workers within an education group using the aggregate distribution or the distribution within an education group.

B.5. Job Flows Across Sectors During the Inflation Period

The first four columns of Appendix Table B.3 use the JOLTS data to report how hires, job openings, layoffs, and quits changed for broad sectors during the inflation period in the United States. Each entry in those four columns of the table represents the percent change in job flows from the JOLTS for each sector between the pre-period (average over the monthly data from January 2016 to December 2019) and the inflation period (average over the monthly data from April 2021 to May 2023). For example, hires increased by 13% in the Education and Health sector during the inflation period relative to the pre-period. Essentially, all sectors experienced a large increase in job openings, a large increase in quits, and a large decline in layoffs during the recent inflation period. The fifth column of the table uses data from the Atlanta Fed Wage Tracker to report how far current real wages are in December 2024 relative to where they were predicted to be based on the 2016-2019 pre-trend. For example, within the Education and Health sector, actual real wages are still 4 percent below predicted real wages based on pre-period trends.

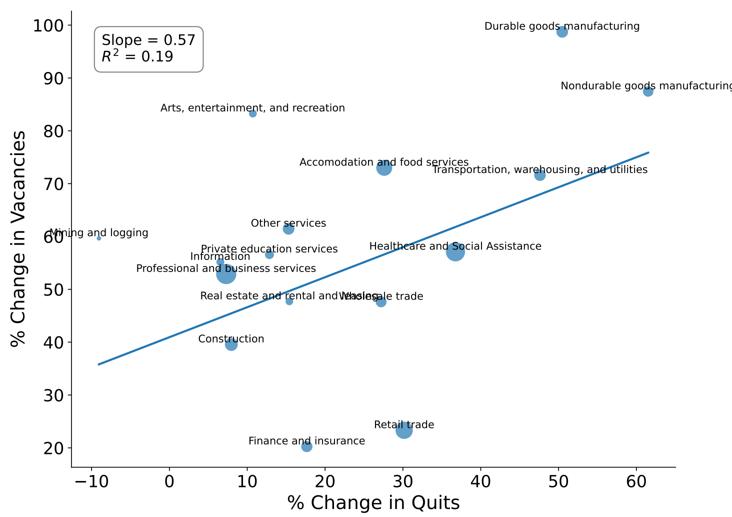
Table B.3: Sectoral Labor Market Flows and Wages During Inflation Period

	% Change in				Real
Industry	**Hires**	**Openings**	**Layoffs**	**Quits**	**Wage Gap**
Construction and Mining	-10	50	-34	-1	-1
Education and Health	13	57	-24	27	-4
Finance and Business Services	5	44	-15	11	-3
Leisure and Hospitality	12	73	-26	20	-3
Manufacturing	38	93	0	57	-4
Trade and Transportation	19	46	-12	35	-4

Notes: The first four columns use data from JOLTS while the last column uses data from the Atlanta Fed Wage Tracker Index. For the first four columns, the table reports the percentage change in hires, job openings, layoffs, and quits between the pre-period and the inflation period. Negative signs reflect decreases during the inflation period relative to the pre-period. The real wage gap in the fifth column is measured as the industry-specific % difference between trend and realized real wages in December 2024.

Appendix Figure B.9 shows the relationship between the change in industry level quits between the pre-period and the inflation period and the change in industry level vacancies between the pre-period and the inflation period. As usual, we define the pre-period as the average over the 2016M1 to 2019M12 data and define the inflation period as the average during the 2021M4 to 2023M12 data. Using cross-industry variation, there is a strong relationship between industry quits and industry vacancies. This is consistent with the prediction of our model. As workers search more, firms respond by creating more vacancies. As documented above, quits during the inflation period primarily represented E-E transitions. If quitters from an industry are more likely to search in that industry, our theory predicts that we should observe a positive relationship between industry quits and industry vacancies during the inflation period. Appendix Figure B.9 provides some potential empirical support for this prediction.

Figure B.9: Industry-Level % Changes: Quits vs Vacancies

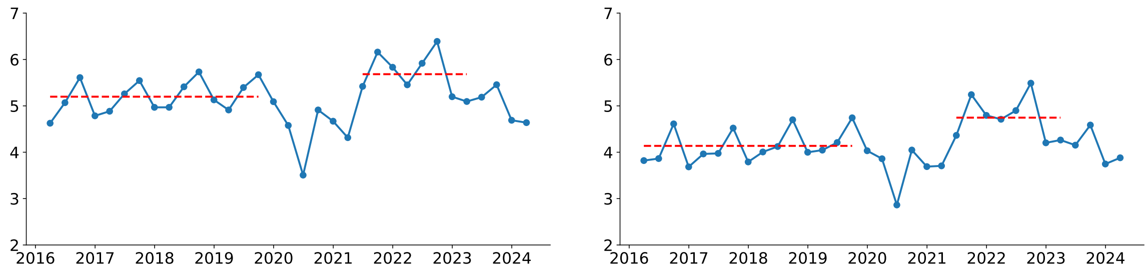


Notes: The figures shows the industry-level relationship between percentage changes in quits (x-axis) and vacancies (y-axis) between the pre-period and the inflation period. Each observation is an industry and is weighted by its pre-period employment. For a given sector, a 1 percent increase in quits is associated with a 0.57 percent increase in vacancies $(SE = 0.31)$.

B.6. E-E Flows, By Education Group

In this subsection, we use data from the LEHD to construct a measure of E-E flows for people who graduated from high school but had no college attendance (HS Graduates) and for individuals who graduated from college (College Graduates+). The LEHD does not measure job-to-job flows by income groups; therefore, we use education as a rough proxy. As seen from the figure, E-E rates jumped for both high school and college graduates. The magnitude of the increase was not statistically different between the two groups.

Figure B.10: E-E Rates, By Education



Panel A: HS Graduates   Panel B: College Graduates+

Notes: The figure above shows the evolution of E-E rate for high school graduates in panel A and college graduates and above in panel B. We use publicly available LEHD data to construct this series.

B.7. ADP Wage Change Distribution, Job-Stayers

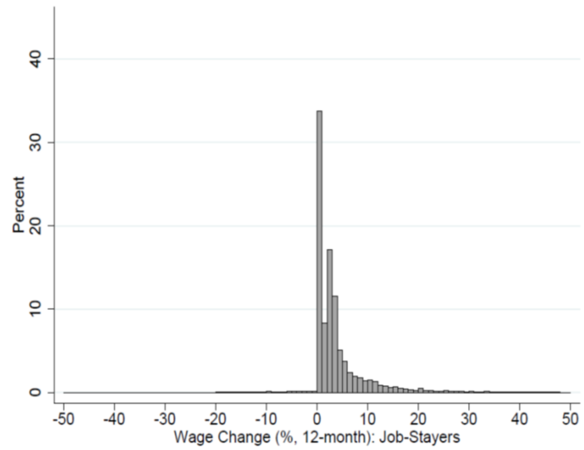
Appendix Figure B.11 shows the year-over-year growth in base wages from the ADP data during the period 2008-2016, as reported in Figure 2 of Grigsby, Hurst, and Yildirmaz (2021). The figure pools together the data for hourly-paid workers and salaried workers. The base wage for hourly workers is their administratively reported hourly wage. The base wage for salaried workers is the administratively contracted base salary per pay period. For example, if the worker is paid bi-weekly, it is their contracted guaranteed bi-weekly pay. See Grigsby, Hurst, and Yildirmaz (2021) for additional details on the sample and wage measures.

B.8. Reported Subjective Well-Being During the Inflation Period, Gallup Data

In this subsection, we use data from Gallup Analytics' *Gallup Poll Social Series* to examine changing measures of subjective well-being between the pre- and post-pandemic periods. Gallup surveys a representative sample of roughly 1,000 individuals each month and asks them about their views on a battery of political, social, and economic questions. Survey respondents are asked questions about their subjective overall and financial well-being in January and April of each year. The Gallup Analytics websites provide summary statistics of responses to their questions for the overall economy and various demographic groups. In addition to reporting data for all respondents, we also exploit their tabulations for representative samples of individuals within three income groups, with roughly one-third of respondents in each group (we refer to these groups as income terciles).[6] We explore two questions – and three

[6]We downloaded the data directly from the Gallup Analytics website, which can be accessed through most university libraries. We accessed the data from the University of Chicago library at https://analyticscampus-gallup-com.proxy.uchicago.edu/Tables/.

Figure B.11: Distribution of Nominal Base Wage Changes, ADP Data 2008-2016



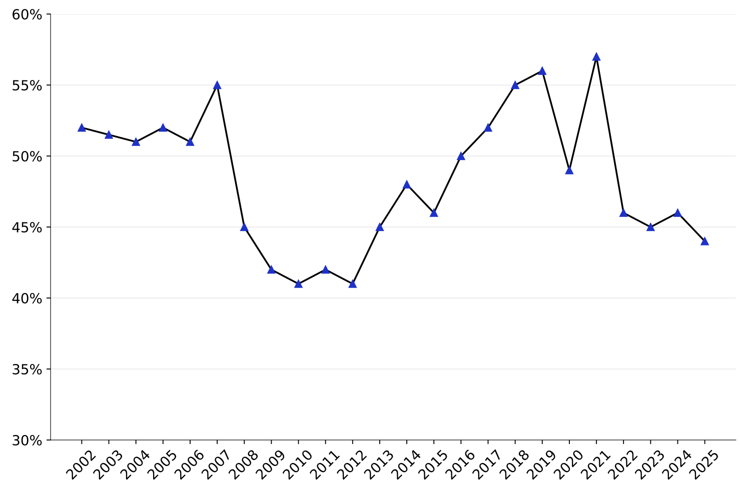
Notes: Figure shows the year-over-year nominal base wage change distribution as reported in Grigsby, Hurst, and Yildirmaz (2021). Data from ADP during the 2008-2016 period and pools together workers paid hourly and who are salaried.

outcomes – designed to measure individual well-being. Below, we detail the questions and the periods in which they were asked.

How would you rate your financial situation today? The answers individuals could provide are "excellent", "good", "only fair", or "poor". We report the share of respondents who indicated that their financial situation is either excellent or good. We refer to this as "Excellent/Good Financial Situation". This question is asked in April every year during the 2002-2025 period, aside from 2003.

In general, are you satisfied or dissatisfied with the way things are going in your personal life at this time? The answers individuals could provide are "very satisfied", "somewhat satisfied", "somewhat dissatisfied", or "very dissatisfied". We create two measures of well-being from this one question. First, we report the share of respondents who indicated that they are either "very satisfied" or "somewhat satisfied" with their personal life. We refer to this as "Satisfied Personal Life". We also separately report the share that says they are "very satisfied" with their life. We refer to this as "Very Satisfied Personal Life". This question was continuously asked in January of every year between 2016 and 2025, aside from 2018. However, the sample sizes of low-income households were sufficiently small in 2022 and 2023 that Gallup did not report the average response to this question for this group in those years. Given that, we exclude 2022 and 2023 when reporting post-pandemic results for these well-being measures for all income sub-groups.[7]

Figure B.12: Excellent/Good Financial Situation Over Time, Gallup Data



Notes: Figure shows the trend in the share of respondents who report that their financial situation was either excellent or good in the Gallup Analytics survey between the 2002 and 2025 period. We impute the 2003 data by taking the average of the 2002 and 2004 data.

Appendix Figure B.12 shows the share of all U.S. respondents who reported that their "financial situation today" was either excellent or good during the 2002 to 2025 period. This measure picks up aggregate conditions quite well. For example, the share of U.S. respondents reporting that their financial condition was excellent or good plummeted during the Great Recession by roughly 10 percentage points. This measure of well-being increased sharply to pre-Great Recession levels as the labor market recovered during the 2014 to 2019 period. The share of those reporting excellent or good financial conditions fell sharply during April 2020 at the onset of COVID and then rebounded in 2021. However, during the inflation period in 2022, individuals' subjective measures of their financial well-being fell back to levels seen in the early part of the Great Recession as their real wages decreased. As real wages remained depressed through 2025, individuals' reported assessments of their financial conditions also remained depressed.

Appendix Table B.4 shows that the self-reported well-being measures for the various income groups are consistent with what happened to their real wages. Specifically, Appendix Table B.4 shows the average reported share for each of our well-being variables for the aggregate economy and for each income tercile in the pre-pandemic and post-pandemic

[7]The "Very Satisfied Personal Life" measure is what is reported in the article cited in the paper's introduction entitled "New Low in U.S. 'Very Satisfied' with Personal Life" found at https://news.gallup.com/poll/655493/new-low-satisfied-personal-life.aspx.

Table B.4: Subjective Well-Being by Income Group Pre- and Post-Pandemic, Gallup Data

Well-Being Measure and Income Group	Pre-Pandemic Period	Post-Pandemic Period	Difference
Excellent/Good Financial Situation			
All Individuals	53.2%	45.2%	-8.0%
Bottom Income Tercile	25.2%	21.0%	-4.3%
Middle Income Tercile	56.2%	40.3%	-16.0%
Top Income Tercile	81.5%	74.2%	-7.3%
Satisfied Personal Life			
All Individuals	86.0%	79.5%	-6.5%
Bottom Income Tercile	75.7%	73.0%	-2.7%
Middle Income Tercile	88.0%	77.0%	-11.0%
Top Income Tercile	94.3%	90.5%	-3.8%
Very Satisfied Personal Life			
All Individuals	55.3%	46.0%	-9.3%
Bottom Income Tercile	42.0%	38.5%	-3.5%
Middle Income Tercile	55.0%	43.5%	-11.5%
Top Income Tercile	69.7%	56.5%	-13.2%

Notes: Table shows the share of respondents from the Gallup Analytics surveys reporting various measures of subjective well-being. See the associated text for a discussion of the subjective well-being questions, the income group definitions, the pre-pandemic and post-pandemic period definitions, and how the data was accessed.

periods. As in the main text, we define the pre-pandemic period as the simple average of the reported shares for each group over the 2016 to 2019 period. For the post-pandemic period, we average the data over the 2022-2025 period for the "Excellent/Good Financial Situation" measure and over the 2024-2025 period for the "Satisfied Personal Life" and "Very Satisfied Personal Life" measures. As noted above, the latter two questions did not have reported shares for low-income individuals during 2022 and 2023.[8] Two facts can be taken away from Appendix Table B.4. First, all measures of well-being fell for all groups between the pre-period and the post-period. Second, all measures of well-being fell less for low-income individuals relative to higher-income individuals. For example, during the pre-period, 81% of high-income individuals, 56% of middle-income individuals, and 25% of lower-income

[8]For the other income groups, the results in Appendix Table B.4 are very similar if we define the post-period as 2022-2025 or 2024-2025. We choose the latter to simplify the table.

individuals reported that their financial situation was either excellent or good. These numbers fell to 74%, 40%, and 21%, respectively, during the post-period. Collectively, the results in this table provide further support for our real wage declines, as highlighted in the main text. For all individuals, their subjective measures of well-being fell as real wages declined. Moreover, those income groups that experienced the smallest real wage declines had the smallest declines in subjective well-being.[9]

B.9. Vacancy Duration During the Inflation Period

Figure B.13 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 are given by:

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

where 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 equation implies that a constant fraction f_t of vacancies is 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:

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

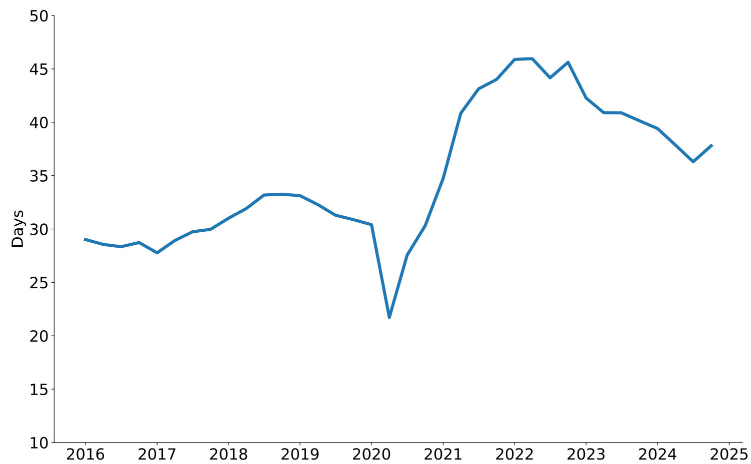
$\tau = 26$ represents the number of working days in a month. Given monthly data on hires and vacancies, the job-filling rate f_t can be estimated directly. The duration of a vacancy, in expectation, is given by $\frac{1}{f_t}$, the object of Figure B.13.

B.10. Corporate Profits Over Time and During the Inflation Period

Panel A of Appendix Figure B.14 shows the ratio of corporate profits to GDP in the United States between 2016 and 2024 (quarterly). We downloaded these data directly from the FRED website. In particular, we used the series Corporate Profits After Tax (without IVA and CCA Adjustments) 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 (Panel B). Between 1950 and 2020, there were only 9 quarters when the corporate profit to GDP ratio exceeded 11% and no quarters when

[9] For many of the well-being measures, the declines were largest for middle income individuals. High income individuals experienced larger real wage losses but also experienced higher financial returns and a larger ability to work from home given their occupations, which offset some of the well-being declines resulting from their declining real wages.

Figure B.13: 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 the implied duration of a vacancy.

the ratio exceeded 12%. The current corporate profit to GDP ratio is at historically high levels. 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 that firm labor market power decreased during the post-pandemic period due to the labor market being tight.

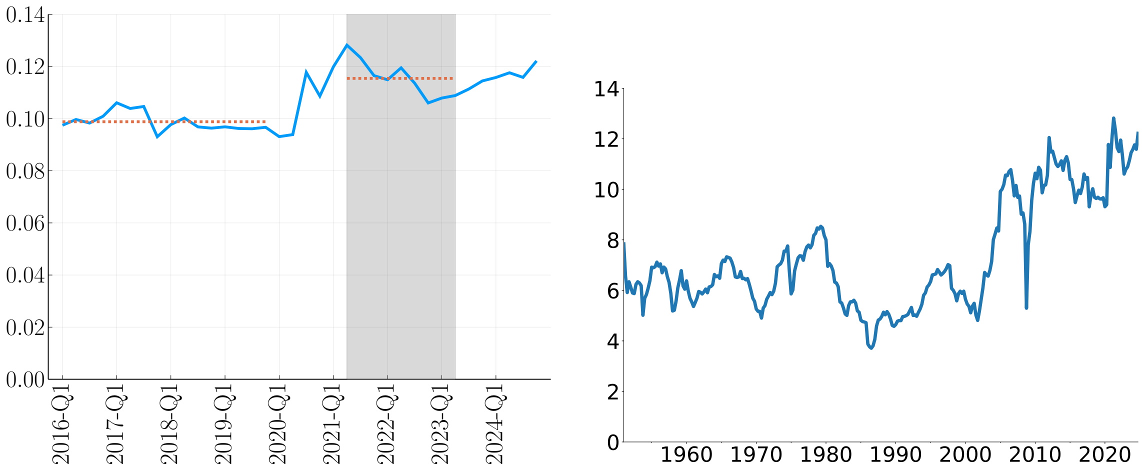
Table B.5: Profit Share and Inflation: 1950-2000

	(1)	(2)	(3)
Unemployment Rate	-0.158^{***}	-0.236^{***}	-0.163
	(0.043)	(0.041)	(0.217)
Unemployment Rate^2			-0.006
			(0.018)
Inflation		0.140^{***}	0.141^{***}
		(0.021)	(0.021)
Constant	7.026^{***}	6.904^{***}	6.697^{***}
	(0.256)	(0.232)	(0.646)
R^2	0.064	0.244	0.244
Observations	196	196	196

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

It should be noted that the corporate profit to GDP ratio was also at historically high

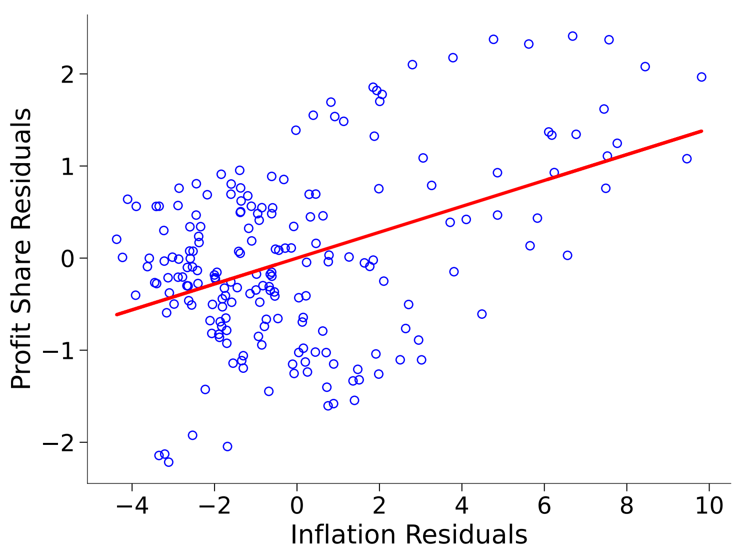
Figure B.14: Quarterly Corporate Profits to GDP Ratio



Panel A: 2016-2024 Panel B: 1950-2024

Notes: The 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.

Figure B.15: Profit Share and Inflation Residuals



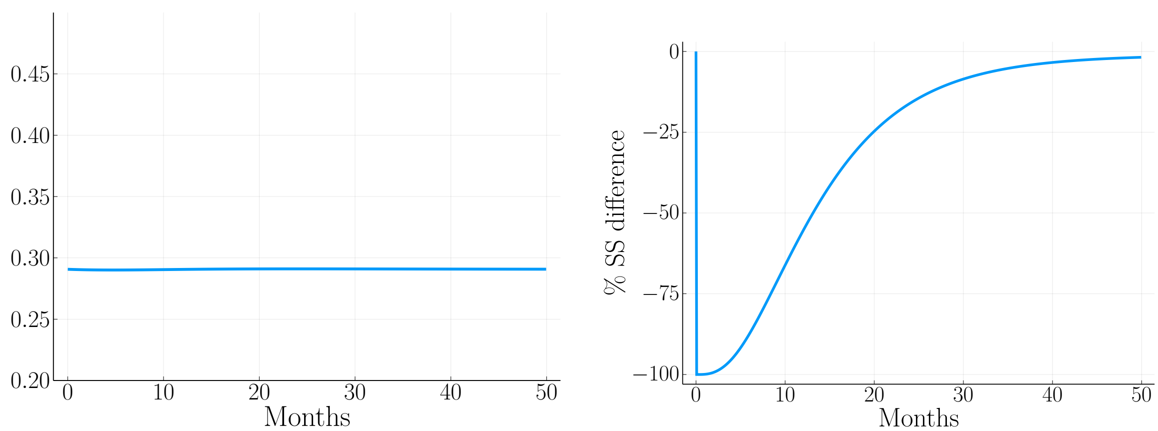
Notes: We residualize both profit share and inflation with the unemployment rate and unemployment rate squared. We regress the profit share residuals on inflation residuals. The sample period for the regression is $1951 - 2000$, predating the secular decline in the labor share in the US.

levels in 1950, 1974, and 1979—all periods during which 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. Appendix Table B.5 regresses the corporate profit to GDP level at the quarterly level on the quarterly averaged unemployment rate and the quarterly averaged inflation rate using quarterly data from 1950 through 1999. As seen from the table, the profit rate falls when the unemployment rate is high. Additionally, the profit rate rises during periods of inflation, even when controlling for the level of the unemployment rate. Appendix Figure B.15 plots quarterly profit share residuals against quarterly inflation residuals. We compute the residuals by separately regressing the profit rate and the inflation rate on both the unemployment rate and the unemployment rate squared. Consistent with our model of sticky wages, periods of high inflation are systematically associated with higher profit rates.

B.11. Additional Counterfactual Results

Appendix Figure B.16 shows the response of the U-E rate and the layoff rate under counterfactual 1. Appendix Figure B.17 shows the response of the U-E rate and the layoff rate under counterfactual 2.

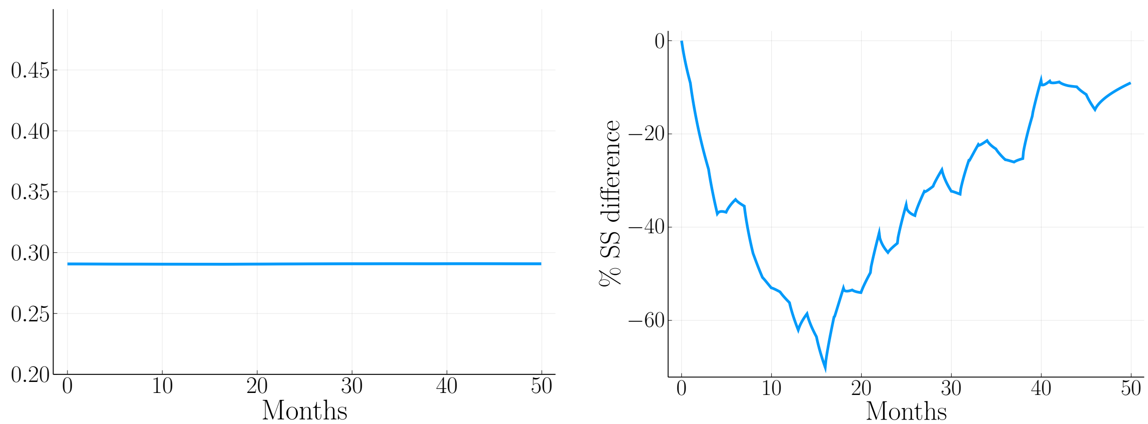
Figure B.16: Additional Labor Market Flows: Counterfactual 1



Panel A: U-E Rate   Panel B: Layoff Rate

Notes: Figure shows the aggregate U-E rate and layoff rate, respectively, in response to the one-time unexpected price level increase analyzed in counterfactual 1 of the main paper. Panel A is reported in levels; panel B is reported as percent deviation from the steady-state.

Figure B.17: Additional Labor Market Flows: Counterfactual 2



Panel A: U-E Rate

Panel B: Layoff Rate

Notes: Figure shows the aggregate U-E rate and layoff rate, respectively, in response to a series of unexpected price level shocks that match the inflation dynamics during the March 2021 to December 2024 period as analyzed in counterfactual 2 of the main paper. Panel A is reported in levels; panel B is reported as percent deviation from the steady-state.

C Identification and Robustness to Parameters

In this section of the appendix, we discuss which moments are important for pinning down different model parameters. We also discuss the robustness of our counterfactual results to several alternate parameter values.

C.1. Sensitivity of Parameters to Moments

As our internally calibrated parameters are jointly pinned down by the set of moments we target in our calibration exercise, in this section we provide an identification analysis by computing the parameter elasticities with respect to different moments, following the procedure in Andrews, Gentzkow, and Shapiro (2017). These values are presented in Table C.1.[10]

While all moments jointly inform the values of all parameters, we can use Table C.1 to (1) confirm that each moment is at least moving one parameter, and (2) use the magnitude of these elasticities to gain some intuition about which parameter is most informed by which

[10]We compute these elasticities by re-solving the model at perturbed parameter values and, when needed, re-simulating the moments. Numerical derivatives use a 20% parameter change: smaller perturbations are more locally accurate but can be dominated by simulation noise while larger perturbations reduce noise in the estimated slope. In addition, due to the stochastic simulation, in order to replicate Table C.1 exactly, the random-number seed must be held fixed in Julia. In particular, since RNG behavior can vary across versions of same packages in Julia, exact replication also requires using the same package versions (as recorded in the Project and Manifest TOML files in the replication package).

Table C.1: Sensitivity of Parameters to Moments

	K	B	η_e	ϕ_k	ϕ_b	ϕ_s	β_+	β_-	λ	ζ	σ_{z0}	σ	γ_e	γ_u
Job finding rate (1-5)	-0.159	-0.029	0.108	0.037	0.027	-0.018	-0.048	0.029	0.055	0.002	0.004	-0.017	-0.016	0.024
Job finding rate (6-10)	-0.115	-0.046	0.108	-0.041	-0.070	-0.008	-0.075	0.192	0.076	0.143	-0.004	-0.009	-0.000	-0.027
Endog. sep. rate (1-5)	-0.183	0.195	0.025	0.029	0.070	-0.042	-0.065	0.122	-0.054	-0.010	-0.002	-0.044	0.022	0.015
Endog. sep. rate (6-10)	0.081	-0.064	-0.036	-0.012	0.006	0.065	-0.062	-0.174	0.243	0.160	-0.002	0.077	-0.032	-0.021
Job-to-Job rate (1-5)	-0.009	-0.020	-0.105	0.060	-0.002	-0.007	0.093	-0.135	-0.062	-0.101	0.001	0.020	-0.005	0.057
Job-to-Job rate (6-10)	0.070	-0.053	-0.097	-0.075	-0.042	0.007	0.101	0.138	-0.029	0.049	-0.006	0.031	0.014	-0.001
Freq. of on-the-job wage increase	0.219	0.018	0.022	-0.140	0.272	0.330	1.357	0.447	-0.246	0.163	-0.072	0.246	0.226	-0.286
Freq. of on-the-job wage decrease	0.000	-0.000	0.000	-0.001	0.001	0.001	-0.001	0.012	0.002	-0.001	-0.001	0.001	0.000	-0.000
Share Δw (0,6)	-0.052	0.041	-0.003	0.014	-0.022	-0.053	-0.207	-0.103	0.142	0.253	0.024	-0.040	-0.020	0.019
Share Δw [6,11)	-0.206	0.198	-0.050	0.045	0.312	-0.053	1.028	0.114	0.266	-0.919	-0.042	-0.151	0.003	-0.128
Share Δw [11,∞)	0.443	-0.381	0.062	-0.111	-0.173	0.307	0.091	0.404	-0.940	-0.417	-0.080	0.333	0.098	0.024
Search-effort wage elasticity	-0.032	0.121	-0.198	0.039	0.023	0.971	-0.030	0.094	-0.062	-0.059	0.001	-0.036	0.027	0.008
p90/p50 real wages (age 25)	-0.686	0.670	0.107	-0.014	0.861	-0.466	-0.839	-0.307	0.784	0.786	0.887	-0.488	0.004	-0.318
p90/p50 real wages (age 25–55)	0.635	-0.559	-0.128	-0.138	-0.404	0.333	0.655	0.655	-0.925	-0.610	0.601	0.380	0.034	0.126
Avg. 30-year wage growth	-0.279	0.433	-0.052	-0.042	0.165	0.021	-0.495	-0.150	0.755	0.311	-0.046	0.037	0.751	-0.427
New wage-unemp. length elasticity	0.175	0.308	-0.038	-0.008	0.033	0.086	0.214	-0.413	-0.049	0.309	0.001	0.069	0.034	0.600

Notes: The figure shows the sensitivity of internally calibrated parameters to targeted moments, following the procedure in Andrews, Gentzkow, and Shapiro (2017). Each cell shows the elasticity of its assigned parameter to its corresponding moment.

moment. Furthermore, although there is no "order of identification" in our joint estimation of parameters, the intuition for how parameters are pinned down is best understood in the following order.

First, we intended for the search effort wage elasticity and the average 30-year wage growth moments to identify the search elasticity parameter, ϕ_s, and the trend productivity of the employed parameter, γ_e, respectively. Consistent with that intuition, Table C.1 shows that the parameter γ_e is most elastic to the average 30-year wage growth moment (i.e., it is less elastic with respect to any other moment), and in turn, no other parameter is more elastic to this moment; i.e., all other parameters are less elastic to this moment than the parameter γ_e (except for λ—one of the wage stickiness parameters—that has almost the same elasticity, but that parameter is identified by the distribution of wage changes as explained below and has a higher elasticity to those moments). Similarly, ϕ_s is most elastic to its intended moment, search-effort wage elasticity, and no other parameter is more elastic to this moment. Thus, ϕ_s and γ_e are identified by their intended moments.

Next, let us put aside these two moments and consider only the remaining "free" ones (so that we do not use the moments above as an explanation for the identification of any other parameters), focusing on the moments intended for identifying the wage rigidity parameters $(\beta_+, \beta_-, \lambda, \zeta)$. For these four parameters, we intended the following five moments: frequencies of on-the-job wage increases and decreases, as well as the three other moments for the share of wage changes at different parts of the wage adjustment distribution. Looking at the corresponding 5×4 block in Table C.1, we observe that, of all the remaining free moments, we observe that β_+ is most elastic to the frequency of on-the-job wage increases—with no other parameter having a higher elasticity to this moment. λ is most elastic to the share Δw in $[11, \infty)$ while the share of Δw $[6, 11)$ induces the highest elasticity (in magnitude) on ζ, and ζ has the highest elasticity to this moment. Finally, both the frequency of on-the-job wage decreases and the share of Δw in $(0, 6)$ have the highest impact on the parameter governing the frequency of opportunities to renegotiate wage decreases, β_-, relative to all other remaining parameters.

Let us next consider the remaining free moments, of which the p90/p50 real wages at age 25 and age 25-55 were intended to identify the standard deviations σ_{z0} and σ_e, and the new wage-unemployment length elasticity was intended to identify the trend productivity of the unemployed γ_u. Applying the same argument above, of the remaining moments, we see that σ_{z0} and σ_z move the most with the two p90/p50 moments, and γ_u moves the most with the new wage-unemployment length elasticity.

At this stage, we are left with the moments related to job finding rates, endogenous separation rates, and job-to-job rates across different deciles of income. Each category has ten moments, but to save space, we have averaged the elasticities of parameters in each category for those above and below the median (i.e., we first compute the true sensitivity matrix and then calculate the average elasticities within each category). As for how we intended these moments to identify the model parameters: the levels of the job finding rate and endogenous separation rates were intended for B and K, and their slope across the deciles for ϕ_b and ϕ_k. Moreover, the level of the job-to-job rate was intended for the scalar in the search cost function, η_e. Investigating the corresponding block of the matrix in Table C.1, we observe that B and K are most elastic to the levels of job finding and endogenous separation rates, while ϕ_b and ϕ_k are elastic to their slopes. Similarly, we observe that η_e is highly elastic to the level of the job-to-job rate.

C.2. Sensitivity of Welfare and V/U Ratio to Model Parameters

To further understand how changes in model parameters affect the welfare losses from inflation, the first column in Table C.2 reports the elasticity of welfare losses to key model parameters under Counterfactual 1. We observe that welfare losses are most elastic to σ_e, the parameter governing the standard deviation of productivity shocks, and β_+, the parameter governing the frequency of on-the-job wage renegotiation subject to finite costs. Both elasticities are negative. Intuitively, higher σ_e implies that the impact of inflation on the wage-to-productivity ratio of workers disappears faster by moving the denominator more prominently. As for β_+, higher wage flexibility on the job reduces the welfare impact of an inflation shock by reducing the expected duration of the shock's impact. While these two parameters have the largest impact on welfare losses, their magnitudes are not too large. Even a 100% increase in σ_e or β_+ would only reduce the welfare losses by 43% and 34%, respectively.

Furthermore, the second column of the table shows the elasticities of the cumulative impulse response (CIR) of the vacancy-to-unemployment ratio with respect to different model parameters. The CIR of V/U moves as expected with parameters that directly affect it; e.g., it decreases with the vacancy posting cost $\tilde{K}$ or exogenous separations δ_0. But what is central to our mechanism is that higher wage flexibility or cost of on-the-job search should mitigate the response of V/U: It is only due to the rigidity of wages that workers increase their on-the-job search in hopes to increase their wages, which is the driving force behind the rise in vacancies. Thus, increases in wage flexibility β_+ or the cost of on-the-job search μ_e should diminish the response of V/U by either affecting the marginal benefit or marginal cost of on-the-job search. Investigating the second column of the table, we observe that both parameters induce sizable negative elasticities on the response of V/U, particularly leading to the conclusion that were wages flexible on the job, we should not observe a sizable response in V/U after an inflationary shock.

C.3. Robustness to Alternative Parameter Values

In this section, we investigate the robustness of our main results to alternative values of several model parameters.

Robustness to Cost Elasticity of on-the-Job Search. Since one of the main mechanisms for the rise in vacancies after an unexpected inflationary shock is higher search among the employed, here we consider alternative values for the parameter governing the elasticity of the cost of search with respect to search effort, ϕ_s. Panels A to D of Figure C.1 present the response of the average E-E rate, the starting markdown of job-changers, aggregate real wages, and the vacancy-to-unemployment ratio, respectively, under different values of ϕ_s. The red line shows the results under baseline calibration. The blue dotted line shows the responses when the value of ϕ_s is cut to half (this corresponds to roughly a 90% increase in the cost elasticity of search effort, $1 + 1/\phi_s$, taking it from a value of around 11.5 to a value of 22). The dotted green line shows the responses for $\phi_s = 1$, which corresponds to quadratic search costs and a very sizable decrease in the cost elasticity of search effort (cutting it from 11.5 to 2; i.e.,

Table C.2: Elasticity of Welfare Losses to Model Parameters (Counterfactual 1)

Parameter	Welfare loss of income decile 5	Cumulative V/U ratio
$\tilde{K}$	0.258	-0.414
$\tilde{B}$	-0.258	-0.049
δ_0	-0.033	-0.569
δ_1	0.001	-0.164
δ_2	-0.001	0.261
μ_e	0.059	-0.374
ϕ_k	0.094	-0.347
ϕ_b	-0.032	0.093
ϕ_s	0.016	-0.019
$\beta_{\Pi^\star}$	-0.012	-0.011
β_+	-0.339	-0.276
β_-	0.054	-0.006
λ_+	-0.146	-0.091
η_+	0.014	0.013
σ_{z0}	-0.008	-0.077
σ_e	-0.433	-0.011
γ_e	0.262	-0.134
γ_u	0.197	0.028

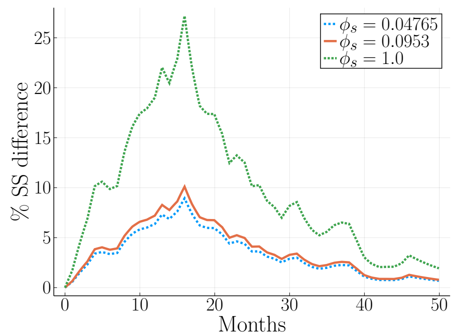
Notes: The table reports the elasticity of welfare losses and cumulative response of V/U ratio to key model parameters under Counterfactual 1.

roughly an 80% decrease). We observe that these sizable changes in the cost elasticity of search lead to only minute differences in the responses of starting markdowns, real wages, and the vacancy to unemployment ratio. The most significant change occurs in the E-E rate when the search cost becomes quadratic. At its peak, there is only a 15 percentage point increase relative to the baseline. However, considering the small value of the E-E rate in a steady state, this results in a difference of roughly 30 to 40 basis points compared to the benchmark, even for such a stark change in the value of the underlying parameter.

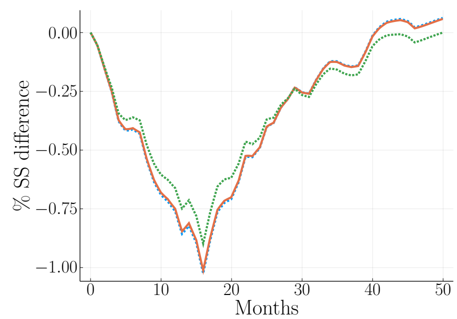
Robustness to Bargaining Power of Employed Workers. Figure C.2 examines the impact of changing the bargaining power parameter τ. The panels report the percent change in aggregate real wages, the E-E rate, and the vacancy-to-unemployment ratio. Again, the results show that the qualitative patterns are robust to alternative values of τ, with only minor quantitative differences.

Robustness to Productivity Trend of the Employed. Figure C.3 shows the robustness of the model to the productivity drift parameter γ_e. The panels display the percent change in

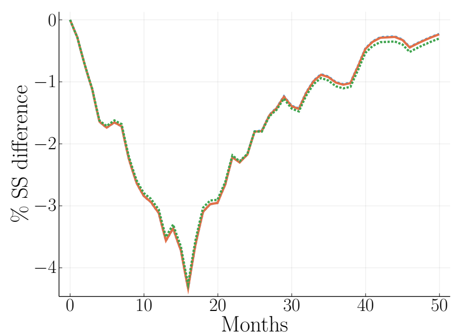
Figure C.1: Robustness to ϕ_s



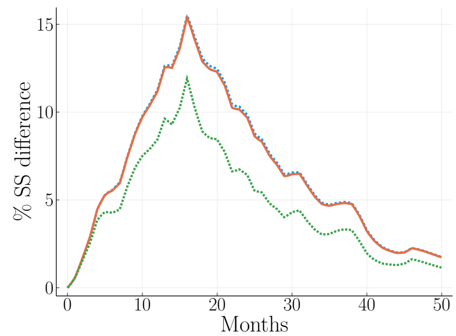
Panel A: E-E Rate



Panel B: Starting Markdown



Panel C: Real Wage



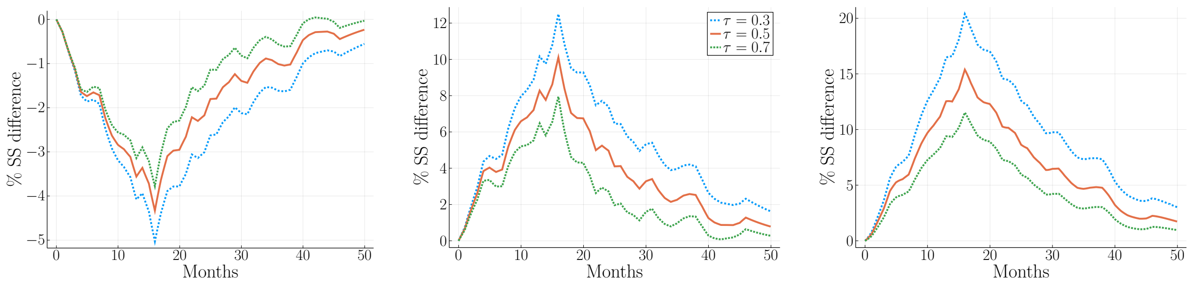
Panel D: V/U Ratio

Notes: Each panel shows the aggregate response of the indicated variable to a sequence of inflation shocks under different values of ϕ_s. Panel A shows the percent change in the E-E rate, Panel B shows the percent change in the starting markdown of job-changers, Panel C shows the percent change in aggregate real wages, and Panel D shows the percent change in the vacancy-to-unemployment ratio. The baseline calibration is shown in red, while alternative values of ϕ_s are shown in blue and green.

aggregate real wages, the E-E rate, and the vacancy-to-unemployment ratio under different values of γ_e. The main observation is that these results are not significantly affected, neither qualitatively nor quantitatively, by these changes in the value of this parameter γ_e.

Overall, these robustness checks demonstrate that our central conclusions regarding the effects of inflation shocks on labor market flows and wages are not sensitive to reasonable variations in the model parameters considered above.

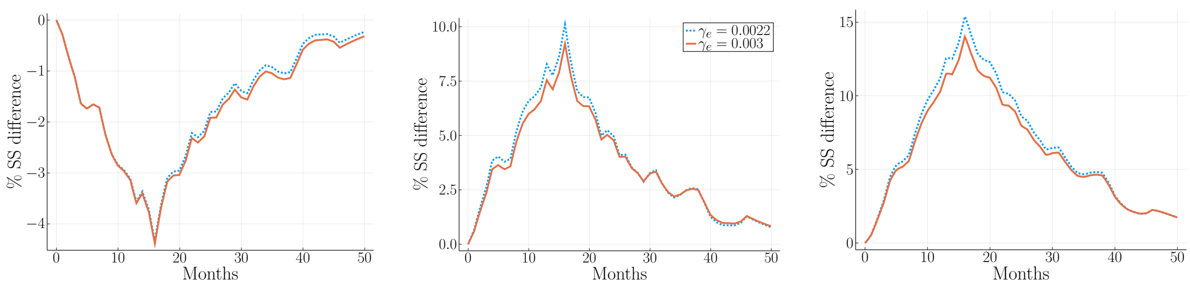
Figure C.2: Robustness to τ



Panel A: Real Wage | Panel B: E-E Rate | Panel C: V/U Ratio

Notes: Each panel shows the aggregate response of the indicated variable to a sequence of inflation shocks under different values of τ. Panel A shows the percent change in aggregate real wages, Panel B shows the percent change in the E-E rate, and Panel C shows the percent change in the vacancy-to-unemployment ratio.

Figure C.3: Robustness to γ_e



Panel A: Real Wage | Panel B: E-E Rate | Panel C: V/U Ratio

Notes: Each panel shows the aggregate response of the indicated variable to a sequence of inflation shocks under different values of γ_e. Panel A shows the percent change in aggregate real wages, Panel B shows the percent change in the E-E rate, and Panel C shows the percent change in the vacancy-to-unemployment ratio.

D Alternate Mechanisms for Rising Vacancy-to-Unemployment Rate

Our quantitative analysis above assumed that the only shock that hit the labor market was an unexpected, temporary increase in the price level. This allowed us to trace the causal effect of a temporary rise in inflation on labor market flows, wages, and well-being. However, inflation itself is an endogenous variable. In this section, we proceed in two parts. First, we explore how wages and other labor market flows respond to other primitive labor market shocks that can cause a rise in the vacancy-to-unemployment ratio. Second, we specifically discuss the labor market implications of the shocks that the literature has identified as the potential causes of the recent inflation.

D.1. Other Labor Market Shocks Through the Lens of Our Model

We begin by exploring a set of other unexpected one-time shocks that can cause the *same* increase in the vacancy-to-unemployment rate. For this appendix section, we make one change to the model in that we now allow for an aggregate productivity shock such that the productivity of a match is $A_t Z_{it}$. In the main text, we just normalized $A_t = 1$ for all t. In this section, we view shocks to A_t as unexpected productivity shocks.

For our counterfactuals, we define the size of the various other shocks we explore so they approximately match our baseline on-impact increase in the vacancy-to-unemployment rate from the one-time 13.5% increase in inflation (shown in Panel A of Figure 5.2) of 23.7%. Specifically, we explore four different one-time unexpected shocks: a positive shock to aggregate productivity (A), 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). Throughout these additional exercises, we maintain the same nominal wage rigidities as in our baseline results.

Table D.1: Comparison of Alternative Mechanisms That Generate High V-U Rate

Variable	Baseline	Higher Agg. TFP	Lower ρ	Lower K	Lower B
% Δ V/U Ratio	23.67	25.04	23.28	22.76	24.37
% Δ EE Rate	31.26	22.15	8.66	11.22	7.31
% Δ UE Rate	-0.01	7.13	14.42	10.62	15.83
% Δ Layoff Rate	-100.0	-98.64	-17.98	59.82	-12.86
p.p. Δ Avg. Real Wage over 12 months	-2.91	4.62	-1.03	0.13	-1.44
p.p. Δ Avg. Real Wage Growth (Stayers)	4.03	1.28	-0.04	0.02	0.01
p.p. Δ Avg. Real Wage Growth (Switchers)	10.19	4.74	-0.22	-0.26	-0.47

Notes: This table compares the effects of different shocks on the labor market. Rows 1-4 are represented as percent differences from the model's steady state levels. The last three rows are represented as percentage point differences from the model's steady state levels. The change in real wage growth relative to steady state (row 5) is measured 12 months after the shock. Real wage growth among stayers is computed conditional on a non-zero nominal change. The change in all other variables are measured on impact. See text for additional details.

Our key finding in this section is that each of these alternative shocks is inconsistent with the broad set of observed labor market dynamics during the 2021-2024 period. The results are summarized in Table D.1. The positive productivity shock provides the closest approximation to the empirical data, with two notable exceptions. First, the productivity shock generates large real wage increases after one year, whereas both the data and our baseline model generate large real wage declines. Second, the positive productivity shock generates a lower increase in the E-E rate, but a larger increase in the U-E rate relative to the baseline model and the data. The lower discount rate, the lower vacancy posting cost, and the lower value of non-employment all successfully generate a large increase in the vacancy to unemployment rate, but fail to match the broad empirical patterns on essentially all other dimensions.

D.2. The Potential Causes of the Recent Inflation

There is growing evidence that the inflation observed in the U.S. between 2021 and 2023 was not caused by rising wages from an overheated labor market. For example, both Lorenzoni and Werning (2023) and Bernanke and Blanchard (2024) provide evidence that the burst of inflation starting in mid-2021 in the U.S. was the result of shocks to prices, holding wages fixed. One piece of evidence supporting their conclusion is that the large rise in aggregate prices predated the modest nominal wage increase. Instead, these authors conclude that the observed inflation resulted from some combination of (i) restricted aggregate supply arising from energy price increases, sectoral reallocation, and pandemic-induced supply constraints, and (ii) increased aggregate demand resulting from the large stimulus enacted during the pandemic. As we discuss next, these two shocks have opposite effects on firm labor demand.

Rising oil prices and supply chain backlogs due to pandemic closures have similar effects on the labor market as a negative aggregate productivity shock. These negative supply shocks will reduce labor demand, given that firms will want to hire less labor. This will put downward pressure on the vacancy-to-unemployment rate, E-E flows, U-E flows, vacancies, employment, and average real wage growth (the opposite of the results in column 2 of Table D.1). A negative supply shock would not generate a hot labor market. Conversely, a positive aggregate demand shock due to increased government spending or pent-up demand from the Pandemic would increase the demand for labor. This would have traditional hot labor market effects of raising the V-U ratio, U-E flows, vacancies, employment, and real wages. These two shocks at the center of explanations for the current inflation have offsetting effects on labor demand. This could be a possible explanation for why aggregate employment (and GDP) did not change much during the current inflation period. If that is the case, the effects of inflation itself could be the primary driver of the real wage dynamics and labor market flows observed during the 2021-2024 period. As seen in the previous section, prior periods of aggregate supply shocks (the early-1950s, the mid-1970s, and the late-1970s) had similar labor market dynamics.

E A Brief Overview of the Computational Algorithm

This section first shows how we introduce separation costs that enhance the numerical stability of the algorithm, and then describes how we solve the model and the calibration strategy.

E.1. Smoothing Layoff and Quit Margins

Without separation costs, a change in the quit and layoff thresholds generates a discrete change in the value of the firm and worker, respectively. The discrete change in the value of each agent introduces jumps in policies and values, creating numerical errors that do not converge to zero as we iterate over the algorithm. To improve the numerical convergence of the model, we assume that workers of type Z face a stochastic quitting cost $\nu_t^h Z$ if they quit to unemployment, and firms face a stochastic layoff cost $\nu_t^j Z$ if they lay off a worker of type Z. Here, ν_t^h and ν_t^j respectively follow a compounded Poisson process such that, with probability $1-\iota\,\mathrm{d}t$, the quitting cost to the worker is $\bar{\nu}^h$ and likewise with probability $1-\iota\,\mathrm{d}t$ the firing cost is $\bar{\nu}^j$ to the firm. With probability $\iota\,\mathrm{d}t$, the costs are respectively drawn from a uniform distribution with support $[0,\bar{\nu}^h]$ or $[0,\bar{\nu}^j]$. We use the notation $\Phi^h(\nu)$ and $\Phi^j(\nu)$ to describe the cumulative distribution functions for the uniform distributions for workers and firms, respectively.

The updated equilibrium conditions of the match are similar to those reported in the main text, with some differences both in the continuation region of the game and at its boundaries. The employed worker's value now satisfies the Hamilton-Jacobi-Bellman (HJB) equation:

$$
\begin{aligned}
\rho H(z,w) = e^w + &\underbrace{\partial_z H(z,w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 H(z,w) - \partial_w H(z,w)\pi^*}_{\text{Law of motion of }(z,w)\text{ during employment}} \\
&- \underbrace{\delta(H(z,w)-U(z)) - \chi H(z,w)}_{\text{Separation and death shocks}} + \underbrace{\beta^\pi\left(H(z,w^*_{\pi^*}(w,z)) - H(z,w)\right)}_{\text{Value of free wage adjustment}} \\
&+ \underbrace{\beta_+ \mathbb{I}_{\{w_b^*(z,w)>w\}} \int \max\left\{H(z,w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^+(\mathrm{d}\psi)}_{\text{Net value of costly upward wage adjustment}} \\
&- \underbrace{\beta_- \mathbb{I}_{\{w_b^*(z,w)\le w\}} \int \max\left\{H(z,w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^-(\mathrm{d}\psi)}_{\text{Net value of costly downward wage adjustment}} \\
&+ \underbrace{\iota\left(\int_0^{\bar{\nu}_h} \max\{U(z)-\nu e^z - H(z,w),0\}\Phi^h(\mathrm{d}\nu) + \Phi^j\left(\max\{-J(z,w),0\}/e^z\right)\left(U(z)-H(z,w)\right)\right)}_{\text{Net value of terminating the match by the firm or the worker in }(w_q(z),w_l(z))} \\
&+ \underbrace{\max_{s_e,w_{jj}}\left\{s_e f(\theta(z,w_{jj}))\left(H(z,w_{jj}) - H(z,w)\right) - e^z \eta_e^{1/\phi_s}\frac{s_e^{1+1/\phi_s}}{1+1/\phi_s}\right\}}_{\text{Expected net value of on-the-job search}},
\end{aligned}
\tag{E.1}
$$

and for all states in which either agent decides to terminate the match, the employed worker's value satisfies $H(z,w)=U(z)$ if laid off ($w>w_l(z)$), and $H(z,w)=U(z)-\bar{\nu}^h e^z$ if the worker chooses to quit ($w<w_q(z)$). The value matching and the smooth pasting conditions are now

given by $H(z, w_l(z)) = U(z)$, $H(z, w_q(z)) = U(z) - \bar{\nu}^h e^z$, $\partial_z H(z, w_q(z)) = \partial_z U(z) - \bar{\nu}^h e^z$, and $\partial_w H(z, w_q(z)) = 0$.

Similarly, the HJB equation for a firm employing a worker at wage w with productivity z in the continuation set is now given by

$$\begin{aligned}\rho J(z,w) = {} & e^z - e^w + \partial_z J(z,w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 J(z,w) - \partial_w J(z,w)\pi^* \\ & + \beta(z,w)\left(J(w_b^*(z,w), z) - J(z,w)\right) + \beta^\pi\left(J(z, w_{\pi^*}^*(z,w)) - J(z,w)\right) \\ & + \iota\left(\int_0^{\bar{\nu}_j} \max\{-\nu e^z - J(z,w), 0\}\Phi^j(\mathrm{d}\nu) - \Phi^h\left(\max\{-(H(z,w) - U(z)), 0\}/e^z\right) J(z,w)\right) \\ & - \left(\delta + \chi + s_e(z,w) f(\theta(z, w_{jj}^*(z,w)))\right). \end{aligned} \tag{E.2}$$

For $w < w_q(z)$, we have $J(z,w) = 0$, and for $w > w_l(z)$, we have $J(z,w) = -\bar{\nu}^j e^z$. The value matching and smooth pasting conditions are $J(z, w_l(z)) = -\bar{\nu}^j e^z$, $J(z, w_q(z)) = 0$, $\partial_z J(z, w_l(z)) = -\bar{\nu}^j e^z$, and $\partial_w J(z, w_l(z)) = 0$.

E.2. Algorithm Summary

E.2.1. Model Solution Strategy. The algorithm begins with strategic normalizations to improve computational efficiency, particularly by recasting state variables in terms of a worker's markdown $\hat{w} \equiv w - p$ and productivity z. This transformation exploits the expected positive correlation between wages and productivity, avoiding unnecessary grid points in the state space. Additional normalizations include $\hat{H}(\hat{w}, z) \equiv \frac{H(w,z)-U(z)}{e^z}$, $\hat{J}(\hat{w}, z) \equiv \frac{J(w,z)}{e^z}$, and $\hat{U}(z) \equiv \frac{U(z)}{e^z}$.

The solution process follows these key steps:

1. **Grid Setup**: Creates equidistant grids for normalized wages $\hat{\boldsymbol{w}} = \{\hat{w}_1, \ldots, \hat{w}_{N_w}\}$ and productivity levels $\boldsymbol{z} = \{z_1, \ldots, z_{N_z}\}$ to define the state space. The complete grid is given by the Kronecker product of these components.
2. **Value Function Iteration**: Uses an iterative approach starting with initial guesses for the value functions of unemployed workers $\hat{U}^0(z)$, employers $\hat{J}^0(\hat{w}, z)$, and employed workers $\hat{H}^0(\hat{w}, z)$.
3. **Continuation Sets and Job-Finding Rates**: In each iteration, the algorithm computes regions where employment relationships continue $\hat{\mathcal{W}}^{h\mathtt{n}}$ and $\hat{\mathcal{W}}^{j\mathtt{n}}$, and determines job-finding rates based on the free-entry condition through $\hat{\theta}^{\mathtt{n}}(\hat{w}, z)$ and $f(\hat{\theta}^{\mathtt{n}}(\hat{w}, z))$.
4. **Policy Functions**: Calculates optimal policies including:
    - **On-the-job search strategy**: Computes workers' optimal target wage $\hat{w}_{jj}^{*\mathtt{n}}(\hat{w}, z)$ when searching while employed and the associated search effort $s_e^{*\mathtt{n}}(\hat{w}, z)$ with Lagrange interpolation. Constructs transition matrices based on these policies, distributing probability mass between grid points using linear interpolation.

- **Bargaining solution**: Solves the Nash bargaining problem between workers and firms to find $\hat{w}_b^{*\mathtt{n}}(\hat{w}, z)$ that maximizes the product of surplus shares with weight τ with Lagrange interpolation. Computes transition matrix based on bargaining outcomes, accounting for both upward and downward wage adjustments through parameters β_+ and β_-.
- **Free wage adjustment**: Calculates transitions from the free-adjustment opportunity matrix that allows wage increases up to $\hat{w} + 12\pi^*$ with probability β_{π^*}.
- **Separation hazards**: Constructs the transition matrix capturing match dissolution from both worker-initiated and firm-initiated separations.

5. **Value Function Updates**: Updates the value functions through finite difference methods and by solving Hamilton-Jacobi-Bellman Variational Inequalities (HJBVI):
   - **Worker value update**: Reformulates the HJBVI for employed workers as a linear complementarity problem (LCP) and solves for $\hat{H}^{\mathtt{n+1}}(\hat{w}, z)$ using specialized LCP solvers. The discretization employs upwinding schemes that handle correlated state variables (see Kushner and Dupuis, 2001; Phelan and Eslami, 2022, for a description of approximating schemes when state variables are correlated).
   - **Firm value update**: Similarly converts the firm's HJBVI into a linear complementarity problem and solves for $\hat{J}^{\mathtt{n+1}}(\hat{w}, z)$.
   - **Unemployed worker value update**: Computes optimal search policies for unemployed workers, including reservation wages $\hat{w}_u^{*\mathtt{n}}(z)$ and search intensity $s_u^{*\mathtt{n}}(z)$ using Lagrange interpolation. Solves the linear system for $\hat{U}^{\mathtt{n+1}}(z)$ with the implicit method.
6. **Convergence Check**: Continue iterations until value functions converge within specified tolerance levels.

E.2.2. Simulation and Calibration. After computing the equilibrium, the algorithm implements:

1. **Simulation**: Generates a random sample of 200,000 workers simulated over 30 years using an approximating Markov Chain (see Kushner and Dupuis, 2001). This produces worker histories with transitions between employment states, wage changes, and productivity shocks.
2. **Data Construction and Moment Calculation**: Organizes the simulation results into a monthly panel dataset that mirrors the structure of the Current Population Survey (CPS) data used for empirical comparison. Computes the same statistical moments from the simulated data as those measured in the actual CPS data.
3. **Parameter Estimation**: Uses Simulated Method of Moments (SMM) with a diagonal

weighting matrix to select the parameter values that minimize the distance between model-generated moments and their empirical counterparts.