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 unexpected inflation on the labor market. Nominal wage stickiness within a match incentivizes workers to engage in job-to-job transitions after an unexpected rise in the price level. Such dynamics lead to a rise in aggregate vacancies relative to unemployment during inflationary periods, associating a seemingly *tight* labor market with *lower* average real wages—two facts observed during the recent inflation period. Calibrated with pre-2020 data, the model can jointly match both aggregate and cross-sectional trends in worker flows and wages during the 2021-2024 period. Using historical data, we further show that prior periods of high inflation were also associated with an increase in vacancies and an upward shift in the Beveridge curve. Collectively, our calibrated model implies that the recent inflation in the United States reduced the welfare of workers through real wage declines and other costly actions, providing a model-driven reason for why workers report disliking inflation. Finally, 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.

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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 rate (V/U), reached historically high levels by mid-2022, as shown in Panel A of Figure 1.1. High inflation, low unemployment, and a high vacancy-to-unemployment rate 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."

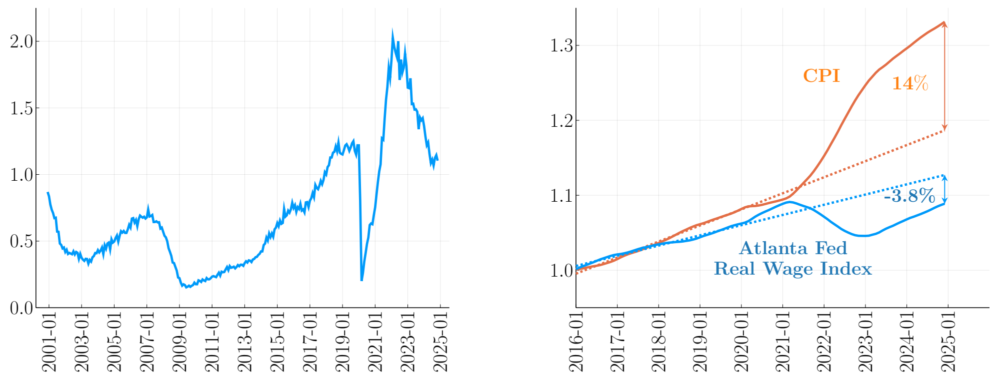
But was the labor market "overheated" during this period? Not according to real wages, which fell sharply with the rise in inflation. As seen in Panel B of Figure 1.1, real wages for the median worker, as measured by Atlanta Fed's Wage Tracker Index, remained persistently below their 2019 levels from 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 vacancy-to-unemployment rate 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 to explore the aggregate and distributional consequences of "inflation shocks" on labor market outcomes and worker well-being.[2] We show theoretically

[1]See Stantcheva (2024) and Afrouzi, Dietrich, Myrseth, Priftis, and Schoenle (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 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. However, in Section 7, we discuss the labor market effects of prominent stories put forth to explain the recent inflation. In particular, we discuss how supply chain disruptions and rising energy prices would *reduce vacancies* and real wages while increases in aggregate

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



PANEL A: VACANCY-TO-UNEMPLOYMENT RATE: 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.

that unexpectedly high inflation induces workers to search more on-the-job providing an incentive for firms to post more vacancies. As a result, our framework shows that a burst of inflation can causally result in both an upward shift of the Beveridge curve by increasing the vacancy-to-unemployment rate and a rise in vacancy durations, giving the appearance of a tight labor market, while simultaneously generating a period 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 upwards 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. As a result, our framework provides a model-driven reason why workers report disliking periods of unexpectedly high inflation (Shiller, 1997, Stantcheva, 2024). Finally, our model provides novel additional real costs of inflation to an economy—such as costly job search and costly

demand from government policies would *increase real wages* and vacancies.

wage renegotiation—stemming from the actions workers take to escape declining real wages.

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.

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. At any given time, based on their current states, workers endogenously 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 menu cost to renegotiate their wage 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) evolves over time according to i.i.d. Brownian motions 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 elasticity of labor market decisions to underlying labor market shocks can differ between high and low wage workers.

On the methodological front, the model requires solving endogenous decisions between

[3]Our framework shares similarities to the model of inefficient separations with nominal wage rigidities found in Blanco, Drenik, Moser, and Zaratiegui (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.

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 market to enter while unemployed, and once within a match, when to renegotiate, when to quit, or when to search for a new job. Firms' strategies are when to layoff their employed workers. A methodological contribution of our paper is to recast the strategic interaction between matched firms and workers as a stochastic non-zero sum game—since the surplus of a match is non-zero—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.[4] The spike in worker 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 markets with higher job-finding rates and lower job-filling rates. This composition shift generates an increase in aggregate vacancy duration consistent with firm's reporting that it was more difficult to hire a worker during this period. The model also predicts that many workers will forgo search and instead choose to engage in costly renegotiation with their firm to increase their real wage.[5] Finally, the reduction in worker 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

[4]Pilossoph and Ryngaert (2023) collected data showing the link between inflation expectations and labor search behavior during the recent inflation period. Likewise, Stantcheva (2024) documents that a subset of workers reported actively searching for a new job as a result of the recent inflation. The results from our structural model are consistent with these empirical findings.

[5]Guerreiro, Hazell, Lian, and Patterson (2024) provide survey evidence documenting that workers were willing to engage in costly renegotiation with their employers to increase their wages during the recent inflationary period. Our structural estimates are consistent with their survey results.

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 the 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. We show that the calibrated model matches additional non-targeted moments such as the fact that low-wage workers face lower average markdowns than higher wage workers consistent with empirical estimates using Danish and Norwegian micro-data (Chan, Mattana, Salgado, and Xu, 2023, Volpe, 2024).

Using the calibrated model, we find that an unexpected temporary inflation shock of the 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 show in Figure 1.1. Additionally, the model matches the fact that real wages fell more for higher wage workers. 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.[6]

We next turn to measuring the effect of the recent inflation on worker welfare. We find that inflation reduced the average welfare of workers in all deciles of the income distribution. However, the welfare losses were larger for higher wage workers who are relatively more inelastic. We estimate that the median worker lost about 20% of one month's income—or about $1,000—from the recent inflation period. To put our numbers in context, we show that the aggregate welfare losses to workers from the recent inflation period are on the same order of magnitude as an exogenous job-destruction shock that increased the U.S. unemployment rate to over 7%. With the unemployment shock, there are large losses concentrated among only a small subset of workers. For the inflation shock, the welfare losses are smaller on average but hit almost all workers. 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 profits rates experienced by US

[6]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.

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 partially offsetting welfare gains from the recent inflation stemming from reduced layoffs.

Looking beyond the inflation surge of 2021, in the penultimate section of the paper we use historical data to show that high inflation rates systematically increase the vacancy-to-unemployment ratio and result in upward shifts in the Beveridge curve. Using Barnichon (2010)'s unified vacancy series, which combines data from the Conference Board's Help Wanted Index and JOLTS, we identify eight periods where 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. Collectively, these results provide additional empirical support for our theory using data prior to the post-pandemic period.

Finally, we conclude the paper with a discussion of the labor market impacts of other shocks through the lens of our model. Some of these shocks have been shown to be important drivers of the recent inflation. For example, an increase in commodity prices and supply chain disruptions should reduce labor demand and put downward pressure on the vacancy-to-unemployment rate and real wages.[7] Conversely, government stimulus and pent up demand from the pandemic should increase labor demand and put upward pressure on both vacancies and real wages. If these shocks had roughly offsetting effects on the labor market, it would be consistent with the fact that our model can quantitatively explain much of the labor market dynamics during the 2021-2024 period with only the decline in real wages generated by the inflation. Collectively, our findings suggest that academics and policymakers should

[7] Lorenzoni and Werning (2023a,b) and Bernanke and Blanchard (2024) highlight the importance of commodity price increases, supply disruptions, and sectoral reallocation in explaining the recent rise in the U.S. price level.

be cautious about viewing the rise in the V/U rate as a sign of an overheating labor market during inflationary periods without holistically looking at other labor market indicators.[8]

As discussed above, 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 vacancy-to-unemployment ratio and the shift in the Beveridge curve. In that sense, 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 employer-to-employer transitions to unemployment-to-employment transitions (E-E/U-E) serves as a key predictor of inflationary pressures. Complementary to their mechanism, 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 the causes and effects of inflationary episodes. Additionally, our work complements Bagga, Mann, Sahin, and Violante (2025)'s recent paper which quantifies a structural model of the labor market to assess the importance of shifting job amenities (such as working from home) on labor market flows and wages during the post-pandemic period. As we discuss throughout, both our story and theirs have empirical support in the data and emerge as the leading explanations for post-pandemic labor market dynamics.

Our work is also related to a set of recent papers showing how worker well-being is affected by recent inflation. Hajdini, Knotek, Leer, Pedemonte, Rich, and Schoenle (2022), Pilossoph and Ryngaert (2023), and Pilossoph, Ryngaert, and Wedewer (2024) all highlight how increased inflation can result in workers searching more for another job. Both Hajdini, Knotek, Leer, Pedemonte, Rich, and Schoenle (2022) and Pilossoph and Ryngaert (2023) use survey data to show that workers with higher inflation expectations increase job search effort. Separately, Guerreiro, Hazell, Lian, and Patterson (2024) fielded a novel survey in early 2024 asking respondents about 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 activity. They find that about one-fifth of all workers engaged in costly actions to raise their wages during the recent inflation period. Our paper shows how jointly including these costly actions in a macroeconomic model of the labor market is necessary to replicate

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

the labor market flows and wage dynamics observed during the recent inflation period.

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 exceeded 14% during this 26-month period. As a way of comparison, the inflation rate in the United States averaged about 2% per year during the 2000-2019 period and averaged just over 3% 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.[9]

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 make a measure of composition-adjusted year-over-year change in the worker's per hour nominal wage on their main job. Given the Atlanta Fed provides a series on nominal wage growth, we create a series of 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 sharply and the unemployment rate increased sharply during the pandemic, they 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 with respect to other labor market outcomes are unchanged whether or not we control for composition shifts between

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

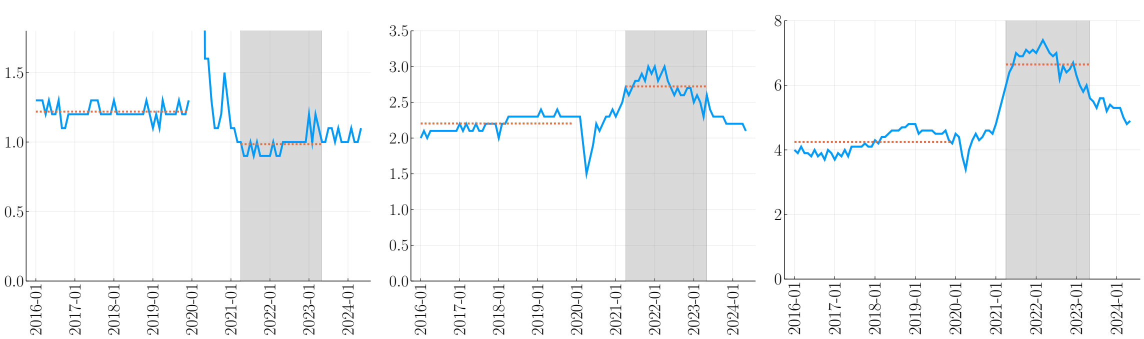
the pre-period and the inflation period; the level or composition of the labor force changed little between our *pre-pandemic period* and our *inflation period*.

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 business 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 layoff, quit, and vacancy rates for the U.S. economy from January 2016 through December 2024 using the BLS's JOLTS data. The shaded years highlight the inflation period. The dashed red lines show the average of the series during the 2016-2019 pre-period and then separately during the inflation period. 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 followed closely 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, which closely follows the time series patterns of the quit rate; firms often post a vacancy to replace workers who quit. 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 sub-section, 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.[10]

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.[11] In the 2016-2019 period, the average E-E rate was 2.30% per month. During the 26-month inflation period, the E-E rate jumped to an average of 2.42% per month (p-value of difference < 0.01). In mid-2022, the E-E rate peaked at 2.55% 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.

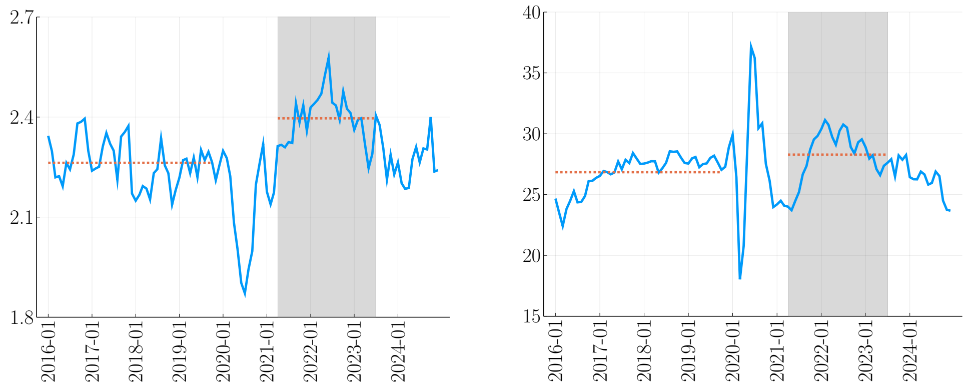
Panel B of Figure 2.2 shows the time series patterns for monthly U-E flows during 2014-2024. The monthly job-finding rate measures the share of unemployed workers who transition to employment during a given month.[12] There was no statistically significant change in

[10] Ellieroth and Michaud (2024) document that quits to non-employment did not increase during the 2021-2023 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 employed workers into unemployment during the 2021-2024 period.

[11] 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.

[12] For ease of replication, we downloaded this series directly from the St. Louis Federal Reserve's Economic Database (FRED). In particular, we downloaded the series "Labor Force Flows Unemployed to Employed" and "Unemployment Level"; both of these series come from the Current Population Survey and are provided at the monthly level. We divide the former by the latter and then take a three month moving average to make the monthly U-E rate.

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). Each observation is a month between January 2016 and December 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 2016Q1-2019Q4 and the 2021Q2-2023Q2 periods. For both series we plot a three month moving average.

the U-E 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 explains the vast majority of unemployment dynamics (Shimer, 2012), changes in the job-finding rate explained relatively little of the unemployment dynamics during the 2021-2024 period.[13]

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

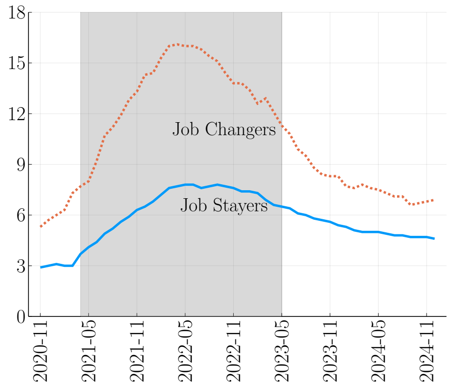
We next use data from *ADP Pay Insights* to examine the relative wage growth of job-changers vs. job stayers during the inflation period. ADP is a payroll processing company that processes payroll for roughly one-fifth of the U.S. labor market. Given the size of the ADP data, ADP can track the components of compensation over time both for workers who remain with the same firm and for workers who transition from one firm to another. As a result, ADP has a much larger sample of job-changers each month than does the CPS.[14] Our analysis with the ADP data spans the 2020 to 2024 period given that ADP Pay Insights only started

[13]We show the decomposition of changes in the unemployment rate to changes in the U-E rate and changes in the layoff margin in Appendix Figure B.4. We thank Joe Hazell for suggesting we add this decomposition to our appendix.

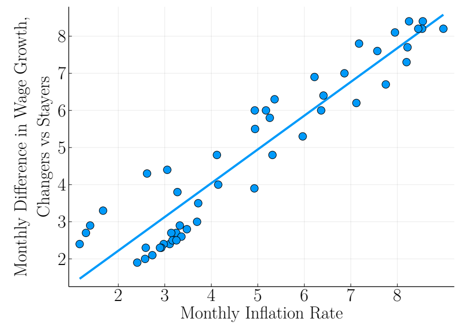
[14]We downloaded the data from ADP Pay Insights directly from `https://payinsights.adp.com/`. For additional information on how the ADP payroll data can be used to measure changes in compensation over time for the US population for both job-stayers and job-changers, see Grigsby, Hurst, and Yildirmaz (2021).

publishing earnings growth data for broad groups such as job-changers vs job-stayers starting in 2020.

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-switchers, dashed line). During the inflation period, the median nominal earnings growth of job changers increased to over 16%. By mid-2024, the median nominal earnings growth of job-changers appears to have stabilized at around 7%. Given that the ADP Pay Insights data started in late 2020, there is no direct way to compare it to a pre-period. However, Grigsby, Hurst, and Yildirmaz (2021) find that median nominal wage growth for job changers in the ADP sample was slightly above 8% during the 2008-2016 period that they analyzed. Given that, the median nominal earnings growth of job-changers in 2024 appears to have returned to pre-pandemic levels. Conversely, the median nominal wage growth of job-stayers peaked at only 8% during the inflation period before returning to about a 4% growth rate by mid-2024; Grigsby, Hurst, and Yildirmaz (2021) find that the average nominal wage growth of job stayers as also about 4% during the 2008-2016 period. 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.[15]

2.5. Heterogeneity in Labor Flows and Wages Across Groups and Sectors

In this subsection, we briefly summarize how the worker flows and wage dynamics documented above vary across workers and sectors. We provide a more extensive discussion in the Online Appendix. Our model will have implications for how workers of differing productivities will respond to unexpected changes in the price level. These patterns will help us assess whether the model predictions are born out in the data.

Real Wage Declines Were Larger for Higher Wage Workers: The Atlanta Fed produces wage series for workers whose wage is in different quartiles of the initial wage distribution. Figure 2.4 shows the real wage trends for workers in the top and bottom quartiles over the 2016-2024 period using the Atlanta Fed Wage Tracker data; the patterns for the second and third quartiles are shown in the Online Appendix. As seen from the figure, real wage declines were much larger for the top of the wage distribution relative to the bottom. Workers in the top quartile of the wage distribution still have a level of real wages in December 2024 that are *lower* than they were in December 2019; relative to trend, these workers currently have real wages that are roughly 6 percent below their predicted level.[16] Workers in the bottom quartile had higher real wage growth on average during the 2016-2019 pre-period (2.1% per year) than did workers in higher wage quartiles. Given that, while workers in the bottom of the wage distribution had real wage levels in 2024 that were higher than they were in late 2019, they still had real wages that were 2.4% below trend as of December 2024.[17]

Quits and Vacancies Increased and Real Wages Declined in All Sectors: There has been a discussion of sectoral reallocation in response to the pandemic. Appendix Table B.2, however, shows that vacancies and quits increased in all broad sectors, layoffs fell in all sectors, and real wages fell relative to trend in all sectors. The patterns suggest that the aggregate patterns highlighted above hold at least at the broad sectoral level.[18]

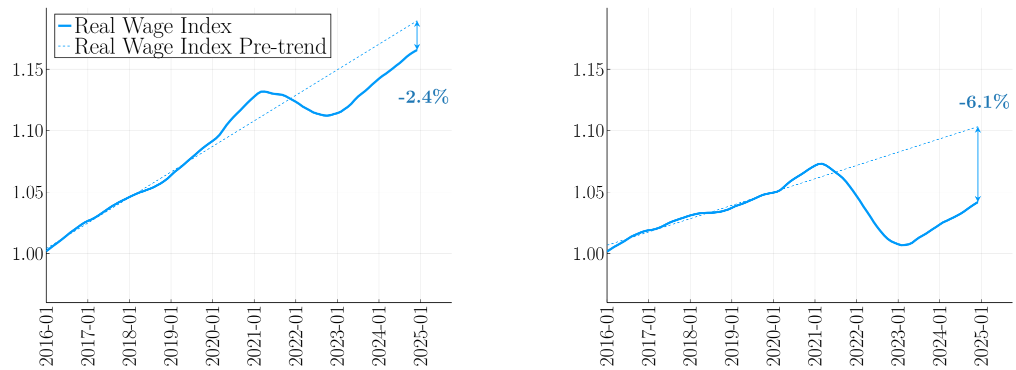
[15] In the appendix, we show that the Atlanta Fed Wage Tracker data also shows that the gap in the wage growth of job-changers relative to job-stayers roughly doubled during the inflation period.

[16] As discussed in Bagga, Mann, Sahin, and Violante (2025), some of the persistent post-pandemic decline in real wage of high wage workers may be attributed to their increased propensity to work from home.

[17] These patters are consistent with the real wage compression documented in Autor, Dube, and McGrew (2024). Whether the real wages for bottom quartile workers are still below trend as of December 2024 depends on the chosen trend rate. For the results in Figure 2.4, we take an approach similar to Autor, Dube, and McGrew (2024) and focus on trends in the few years prior to 2019. In the appendix, however, we show results where the trends are defined over the longer 2000-2019 period.

[18] We explored whether E-E rates differed by income groups but did not have enough power to detect any differences. The LEHD tracks E-E flows for different education groups. We show these results in the Online

Figure 2.4: Real Wage Growth, By Wage Quartile



Panel A: Bottom Income Quartile Panel B: Top Income 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 shows the 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.

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. Our goal is to have the model match both the time-series patterns in labor market outcomes on average and also match the heterogeneous patterns across workers of differing types. The model mixes elements of modern theories of labor market flows with frictions in nominal wage adjustments and lack of commitment on the side of both workers and firms. The interaction of these two frictions leads to infrequent wage adjustments and inefficient labor market flows in response to aggregate shocks.[19] In such an environment, a burst of inflation reduces workers' real wages which incentives workers to engage in costly renegotiation for higher wages with their current employer or to engage in on-the-job search to secure an updated real wage. The additional worker search effort results in firms posting more vacancies. Lastly, the inflation makes incumbent workers a bargain for their employers resulting in them reducing layoffs at the same time their profits increased. Altogether, through the lens of our model, an unexpected period of inflation generates declining real wages, a burst of quits, higher E-E flows, higher vacancies for employed workers and declining layoffs,

Appendix. E-E flows jumped sharply for both low and higher educated households.

[19] Our framework shares similarities to the model developed in Blanco, Drenik, Moser, and Zaratiegui (2024).

consistent with the U.S. labor market patterns for the recent inflationary period documented in the prior section.

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 ($E_{it} = 0$), which is denoted by the indicator function $\mathbb{I}(E_{it} = 1)$ that is equal to 1 when the worker is employed. 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 the price of the homogeneous consumption good is exogenous.

Exogenous Worker Shocks. Each worker is subject to an idiosyncratic productivity shock, Z_{it}, that evolve over time as follows. When workers are born, they draw their productivity from a log-normal distribution with mean μ_{z0} and standard deviation σ_{z0}. After birth, worker-specific productivity Z_{it} follows a Brownian motion with drift:

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

where the drift $\gamma(E) = \gamma_e \mathbb{I}(E = 1) + \gamma_u \mathbb{I}(E = 0)$ potentially depends on the employment state. For example, while employed γ_e may be positive reflecting on-the-job human capital accumulation and while unemployed γ_u could be negative reflecting the depreciation of skills while not working. We refer to workers with differing Z's as being workers of differing types.

Production Technology. While employed in a match, worker i produces AZ_{it} units of output where A is an aggregate productivity measure. Such a worker then receives a real wage $W_t = \tilde{W}_{it}/P_t$, where $\tilde{W}_{it}$ is the nominal wage and P_t is the price level with growth rate denoted by π.[20] To start, we assume A is normalized to 1, and in Section 7 we shock A to assess how the model responds to aggregate productivity shocks. While unemployed, worker i receives a flow real income of $BZ_{it}^{\phi_B}$, which captures the flow value of non-employment.[21]

[20]We abstract from modeling match specific productivity with our assumption of homogeneous firms. Due to computational burden, we stayed away from solving the model with both heterogeneity in worker productivity (differences in absolute advantage) and match specific productivity draws (differences in comparative advantage). We made a choice to prioritize the worker heterogeneity to analyze the distributional effects of the recent inflation. Exploring the implications of our broad framework with match-specific productivity is a worthy avenue of future research.

[21]The fact that the value of non-employment is in real terms is consistent with the findings of Chodorow-Reich and Karabarbounis (2016a). They find that most of the value of non-employment is due to the value of non-working time (e.g., the value of leisure or home production) which is not subject to nominal rigidities.

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. Conversely, when $\phi_B > 1$, employed high-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 $\phi_K < 1$, vacancy posting costs will be proportionally smaller for high-productivity workers. Conversely, 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 $\eta(E) = \eta_e \mathbb{I}(E = 1) + \eta_u \mathbb{I}(E = 0)$ 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 market 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 only visit 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).[22] 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 getting 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-changers. 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 the 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 possibility of a "free" wage increase. These free wage increases reset worker real wages to their Nash-bargained level with the constraint that the nominal wage change be in the range of 0 and $\Delta\bar{w}_{\pi^*}$. This process proxies for the fact that most employers evaluate their worker 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, like a 2 or 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 $\Delta\bar{w}_{\pi^*} = \pi^*$, which is the steady-state trend inflation in the economy.[23] 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^+ draw from an exponential distribution—measured in units of utility—to initiate a wage renegotiation process with their employer to increase their nominal wages to their unconstrained Nash bargained level.[24] This

[22] 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.

[23] 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.

[24] It should be noted that we treat search costs and renegotiation costs as being two distinct decisions. However, workers could search for another job and bring their external offer back to their original firm to

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 start 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 according to the Nash Bargaining solution, where the worker's bargaining power is denoted by τ and the outside option in case bargaining fails is the dissolution of the match.

It is worth noting that nominal rigidities in this model only occur with respect to wages of workers within a current match. As is common in the literature, we assume that wages of new hires are perfectly flexible. This 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.[25]

Agents' Objectives. Workers born at period t maximize expected utility and discount the future at rate ρ. They have linear preferences over flow income Y_{it} net of search effort, $(Y_t - S_t)\mathrm{d}t$, 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.[26]

facilitate a renegotiation of their current wage. In this case, the renegotiation costs could stem, in part, 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 the potential link between the two, we group these costs together when assessing the welfare costs of inflation on worker well-being.

[25] Kudlyak (2014) and Bils, Kudlyak, and Lins (2023) provide evidence that new hire wages are more flexible than incumbents. Gertler, Huckfeldt, and Trigari (2020), Grigsby, Hurst, and Yildirmaz (2021), and Hazell and Taska (2024) find that new hire wages are just as rigid as that of incumbents. As with incumbent workers, the flexibility of new hire wages may be asymmetric between periods when nominal wages should fall relative to when nominal wages should increase. Hazell and Taska (2024) actually provides evidence for such asymmetry. Given we are looking at periods of flexibility on the upside, we assume that new hire wages are more flexible during this period consistent with the data show in Figure 2.3.

[26] To improve numerical convergence of the model, we also assume workers of type Z_t face a stochastic quitting cost and firms face a stochastic cost of laying off a worker of type Z_t. These stochastic termination costs for both workers and firms are introduced to smooth their value functions to improve numerical convergence of the model; We set them to arbitrarily small levels. We suppress the notation for these smoothing parameters in the main text to simplify exposition but discuss them more fully in the calibration section of the Online Appendix.

3.2. Values and Equilibrium Conditions

In this subsection, we derive the conditions that characterize the equilibrium of this economy. 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) market. 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. As a reminder, search is directed so that each sub-market is defined by the offered log real wage (w) and the log productivity of the worker that firms are trying to hire (z).

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

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

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 $\hat{w}_u$, which determines 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 with the firm's value. Thus, equation (5) can be also 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

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

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 bargained 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 subject to the constraint $w_{\pi^*} \in [0, \pi^*]$.

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 or not to lay off the worker. We denote by $\mathcal{W}^{j*}$

the set of (z, w) pairs where the firm chooses to continue the match.[27] For each productivity level z, we defined $w_l(z)$ 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 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 bargaining 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 the firm and the worker are both 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:

$$\begin{aligned}\rho H(z,w) = e^w + &\underbrace{\partial_z H(z,w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 H(z,w) - \partial_w H(z,w)\pi^*}_{\text{Law of motion of } (z,w) \text{ during employment}} \\ &- \underbrace{\delta(H(z,w) - U(z)) - \chi H(z,w)}_{\text{Separation and death shocks}} + \underbrace{\beta^\pi \left(H(z, w^*_{\pi^*}(w,z)) - H(z,w)\right)}_{\text{Value of free wage adjustment}} \\ &+ \underbrace{\beta^+ \mathbb{I}_{\{w_b^*(z,w) > w\}} \int \max\left\{H(z, w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^+(\mathrm{d}\psi)}_{\text{Net value of costly upward wage adjustment}} \\ &- \underbrace{\beta^- \mathbb{I}_{\{w_b^*(z,w) \leq w\}} \int \max\left\{H(z, w_b^*(z,w)) - H(z,w) - \psi e^z, 0\right\} \Psi^-(\mathrm{d}\psi)}_{\text{Net value of costly downward wage adjustment}} \\ &+ \underbrace{\max_{s_e, w_{jj}} \left\{ s_e f(\theta(z, w_{jj}))\left(H(z,w_{jj}) - H(z,w)\right) - e^z \eta_e^{1/\phi_s} \frac{s_e^{1+1/\phi_s}}{1+1/\phi_s} \right\}}_{\text{Expected net value of on-the-job search}}, \end{aligned} \tag{9}$$

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,

[27] As in Blanco, Drenik, Moser, and Zaratiegui (2024), we require the continuation set to be a weakly dominating strategy to ensure the uniqueness of equilibrium.

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:

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

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 under employment $H(z, w)$ 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

$$\begin{aligned}\rho J(z, w) = {} & e^z - e^w + \partial_z J(z, w)\gamma_e + \frac{\sigma^2}{2}\partial_z^2 J(z, w) - \partial_w J(z, w)\pi^* \\ & + \beta(z, w)\left(J(w^*_b(z, w), z) - J(z, w)\right) + \beta^\pi \left(J(z, w^*_{\pi^*}(z, w)) - J(z, w)\right) \\ & - \left(\delta + \chi + s_e(z, w) f(\theta(z, w^*_{jj}(z, w)))\right).\end{aligned} \tag{12}$$

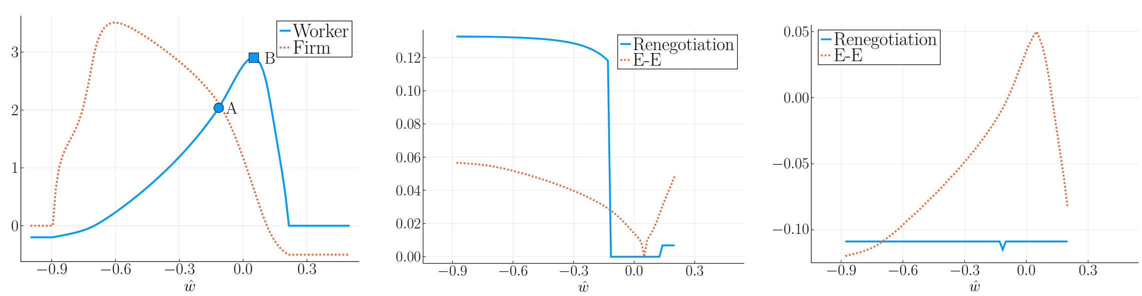
For $w \notin (w_q(z), w_l(z))$, we have that $J(z, w) = 0$. The corresponding value-matching and smooth-pasting conditions are now given by $J(z, w_l(z)) = J(z, w_q(z)) = \partial_z J(z, w_l(z)) = \partial_w J(z, w_l(z)) = 0$.

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 some 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, $\hat{w} \equiv w - z$.

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 during either renegotiation (solid line) or when making an E-E transition (dashed line).

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 who 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 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. This reflects a trade-off. 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 come back to this feature when explaining wage renegotiation and E-E policies below.

The dashed red line in Panel A represents the firm's value from employing a worker of type z at differing wages. The firm value is also hump-shaped in the markdown. When the markdown is large, workers will quit to unemployment reducing firm value (very few workers tend to be in this range). Throughout most of the range, firm value decreases with higher wages, reflecting the direct relationship between wages and profits when productivity is held constant.[28]

The solid blue line in Panel B shows the hazard rate at which workers pay the fixed cost

[28] Notice that firm values turn negative for higher wages given that we impose small stochastic layoff costs to improve the numerical convergence of the model. Likewise, worker values turn negative for lower wages because we impose some stochastic quitting costs. We discuss the addition of these costs to worker and firm values in the Online Appendix.

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)), workers would be reset to point A. Consequently, workers with markdowns between points A and B optimally choose not to renegotiate, as it would lower their wage and value. When the markdown dips below point A, workers' willingness to pay the renegotiation cost discretely increases. The solid blue line in Panel C shows that when workers with this particular productivity renegotiate, they always return to a wage markdown of about 11% which corresponds to point A in Panel A.

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 because of 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 the red dashed line 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 flow 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. This implies that $\hat{w}^*_{jj}$ 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, firms are made better off from this direct effect as their profits increase within the match, 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. This welfare gain stemming from reduced layoffs in response to the inflation can offset a portion of the welfare losses experienced by workers resulting through other channels. This effect is largest for worker's whose initial markdown is to the right of point B. For them, their value of employment increases on net as their 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 the 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 again 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 $\hat{w}_L$ that fell by an amount Δ_L 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:

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

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. As discussed above, 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:

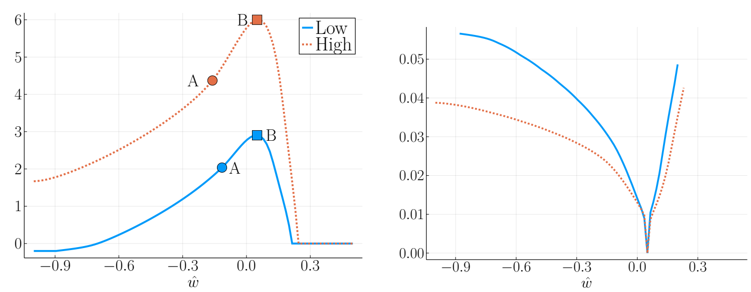
$$\mathcal{V} = \left(\frac{J(z, \hat{w}_{jj}(z, \hat{w}_L - \Delta_L))}{Ke^{\phi_K z}} \right)^{1/\alpha} s(z, \hat{w}_L - \Delta_L). \tag{14}$$

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.

Finally, the expected duration of vacancies, measured by the inverse of the job-filling rate, will also increase in response to an inflationary shock: As inflation causes workers to shift toward searching in markets with lower job-filling rates, the aggregate duration of E-E vacancies increases. In conclusion, all workers whose markdown is below point B will shift to sub-markets characterized by more vacancies and longer durations following an unexpected burst of inflation. 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.

Heterogeneity Across Worker Types. All of the above discussion focused on how the model operates for a worker of a given z. Figure 3.2 extends this analysis by showing the worker values and E-E transition rates for two worker types from our calibrated model: a low z worker (solid blue line) and a high z worker (dashed red line). Two key patterns emerge from this comparison. First, our calibrated model finds that the job ladder is longer for higher productivity workers. These workers transition from unemployment to employment, on average, at a lower markdown (point A is more to the left for higher productivity workers). Similarly, their value-maximizing markdown is also higher (point B is more to the right for higher productivity workers). Second, our calibrated model finds that the slope of E-E transition rates is steeper for lower productivity workers. This greater sensitivity implies that low-productivity workers will experience larger increases in E-E transitions in response to inflationary shocks. These heterogeneous responses stem from our calibration described in the next section, which finds that $\phi_B < 1$ and $\phi_K > 1$. These parameter values imply that low productivity workers are more elastic to labor market shocks relative to high productivity workers.

Figure 3.2: Worker Value and E-E Rates Across Different Worker Types



Panel A:
Worker Values

Panel B:
E-E Rates

Notes: This figure shows worker values (Panel A) and E-E Rates (Panel B) as a function of the wage markdown for workers with low productivity (blue solid line) and workers with a higher productivity (red dashed line). The circles and squares on the worker value lines in the left panel correspond to points A and B, respectively, in Figure 3.1.

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. A detailed discussion of our calibration algorithm can be found in the Online Appendix.

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, Larrimore, Park, and Tranfaglia, 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 from Petrongolo and Pissarides (2001). In order to satisfy Hosios condition (Hosios, 1990), we also set the worker's bargaining power τ to 0.5, which is standard in the literature. 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
π^*	Trend inflation	0.002	Annual inflation rate 2000-2019
$\Delta\bar{w}_{\pi^*}$	Target inflation	0.002	Annual inflation rate 2000-2019

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.

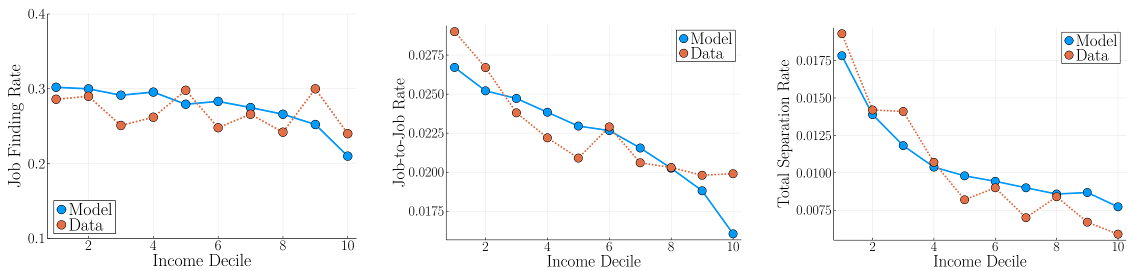
Productivity process. σ_{z0} is chosen to match a P90-P50 weekly earnings ratio for workers aged 25-27 of 2.12 between 2016 and 2019 from the CPS. For productivity dynamics, we set the productivity drift while employed to $\gamma_e = 0.002$ per month to capture a 70 percent growth rate in average earnings of employed workers over 30 years (Alves and Violante, 2023). 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 0.039 to match the P90-P50 weekly earnings ratio for workers aged 25-55.

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	0.04
σ_{z0}	Std. of initial productivity	0.579
Labor Market Flows		
B	Non-employment production	0.973
ϕ_b	Elast. of unemp. income wrt. z	0.71
K	Vacancy cost	9.663
ϕ_k	Elast. of vacancy cost wrt. z	1.419
η_e	Search cost scale when employed	6.397
ϕ_s	Elast. of search cost	0.103
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	0.133
β_-	Prob. of negative wage renegotiation	0.007
λ	Prob. mass at zero for menu cost dist.	0.864
ζ	Rate parameter of menu cost dist.	0.647

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 why 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, respectively, report that their unemployment spell originated from a quit, a layoff or another reason. We interpret separations due to other reasons as being 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 $\delta(Z) = \delta_0 + \delta_1 \exp(\delta_2 Z)$ where we use individual earnings prior to the separation as our measure of Z. Formally, to set these three parameters, we target the separation rate into unemployment due to "other reasons" across the weekly earnings distribution. Exogenous separations fall sharply with respect to worker productivity.

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).

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. To reproduce the aggregate level of U-E flows in the model, we first normalize the search cost of the unemployed to $\eta_u = 1$ as noted above. Next, 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. 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 48%, which is in the range reported by Chodorow-Reich and Karabarbounis (2016b).

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 cost 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 be declining with income. However, in the data, the U-E rate is relatively constant with income. The calibration rationalizes this pattern by estimating that $\phi_B < 1$ which implies that more productive workers lose more—in relative terms—by staying in the unemployment state. In other words, the market wage of low productivity workers is on average closer to their value of non-employment while the gap between market wages and the value of non-employment is on average larger for high productivity workers. As a result, high-productivity workers search more intensively while 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. In particular, the paper shows the following: (i) essentially no job-stayer gets a nominal wage cut during a year, (ii) about one-third of job-stayers get no nominal wage change during a given year, (iii) about 10% of workers get annual wage changes between 0 and 2%, (iv) about one-third of workers get an annual wage change of about 2 or 3%, and (v) there is a long tail of larger wage changes with a drop-off after 3%. As discussed above, this distribution is what motivates us to include both a Calvo and menu cost component to wage adjustments with an asymmetry between wage increases and wage cuts. 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 resources practices that nominal wages have the opportunity to costlessly adjust once a year.

The heterogeneous menu cost part of the model helps us match the long tail in wage changes of job-changers above 3%. The endogenous renegotiation process has two parts. First, in each period, workers receive (i) with a Poisson arrival rate $\beta^{+}dt$ an opportunity to draw a renegotiation cost for increasing their wage and (ii) with a Poisson arrival rate $\beta^{-}dt$ a separate opportunity to costlessly renegotiate their wage downward. Conditional on $\beta^{+}dt$, the renegotiation cost for 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 rate parameter of the exponential distribution while the parameter λ governs the size of the mass point at zero.[29] Along with β^π discussed above, the parameters β_+ and β_- directly inform the frequency of positive and negative wage changes, respectively. The former is calibrated to 0.133, implying an actual monthly frequency of positive wage changes of 6.1% 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 needed to match the observed small share of negative wage changes found in Grigsby, Hurst, and Yildirmaz (2021). λ and ζ are parameterized to match the share of small versus large wage changes in the ADP data (e.g., a larger expected menu cost shifts the distribution toward larger changes).

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	0.061
Share $\Delta w_b \in (0, 6)/(0, \infty)$	0.73	0.69
Share $\Delta w_b \in [6, 11)/(0, \infty)$	0.14	0.15
Share $\Delta w_b \in [11, \infty)/(0, \infty)$	0.13	0.16
Search effort-wage elasticity	-0.52	-0.5
P90/P50 real wages (age 25)	2.12	2.09
P90/P50 real wages (ages 25-55)	2.57	2.53
Avg. 30-year wage growth	0.7	0.72
New wage-unemployment length elasticity	-0.006	-0.006

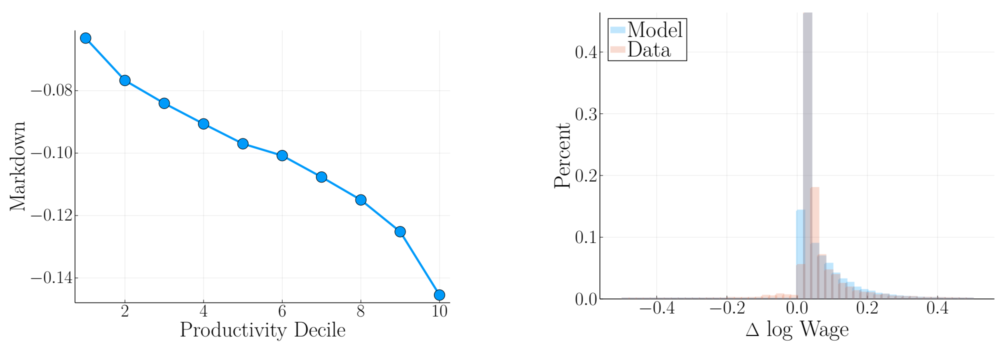
Notes: The table shows the set of moments (excluding the flows, the results for which are reported in Figure 4.1) that were targeted for calibration.

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

[29] 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%.

result, experience lower wage markdowns on average. This prediction of our model aligns well with the findings of Chan, Mattana, Salgado, and Xu (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 change, found in the ADP data. We target that only 6% of job-stayers receive a wage change during a given month. 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, the model matches the full distribution of nominal wage changes well. For example, our model generates the large spike in nominal wage changes at 2% as seen in the data. We find it encouraging that our parsimonious parameterization matches the full distribution of nominal wage changes well.

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. Additionally, this first analysis will give us an upper bound on the effects of the inflation on labor market flows, as it approximates a scenario where workers immediately anticipate the full trajectory of future inflation as of April 2021.

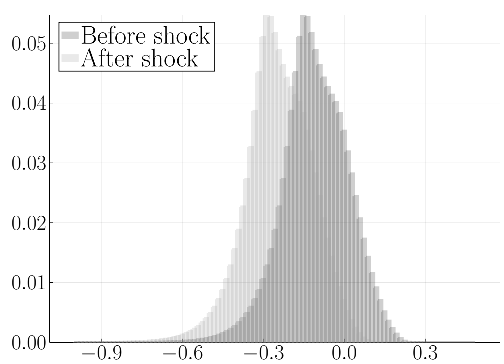
Our second exercise explores a more conservative counterfactual by showing how wages and labor market flows respond to a series of unexpected inflation shocks that replicate the actual inflation path observed during the 2021-2024 period. Throughout this period, we impose that workers consistently maintain expectations of 2.2% annual inflation going forward, implying that in each period the realized inflation rate is an unexpected surprise. Thus, this experiment assumes that there was no change in inflation expectations during this period and, as a result, produces a lower bound on the response of labor market flows, while likely providing a more accurate assessment of the actual welfare effects. To that end, 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. Throughout, we explore the response of aggregates as well as the responses of workers in different parts of the initial wage distribution.

5.1.1. Wage Markdowns On Impact. Figure 5.1 shows the distribution of wage markdowns in the economy right before (in dark gray) and right after (in lite 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 right of point B in our illustrative example in Figure 3.1.

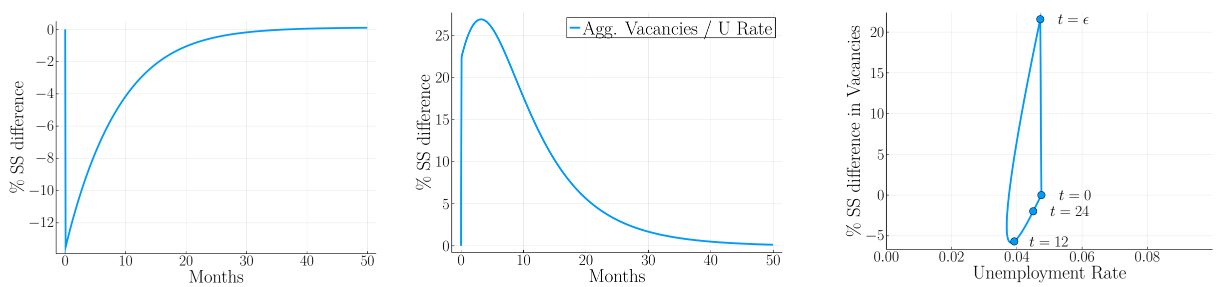
Figure 5.1: Markdown Distribution Before and After Inflation Shock



Notes: The 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 back 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. Most of this variation arises from a spike in posted vacancies, since the unemployment rate slowly declines as firms reduce layoffs before returning to its steady-state value.[30] Given the small movements in the unemployment rate, essentially all of the increase in the V/U rate is driven by an increase in vacancies. The vacancy-to-unemployment rate also returns to steady-state levels within about 30 months.

Figure 5.2: Real Wage, Vacancy-to-Unemployment Rate, and Beveridge curve



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

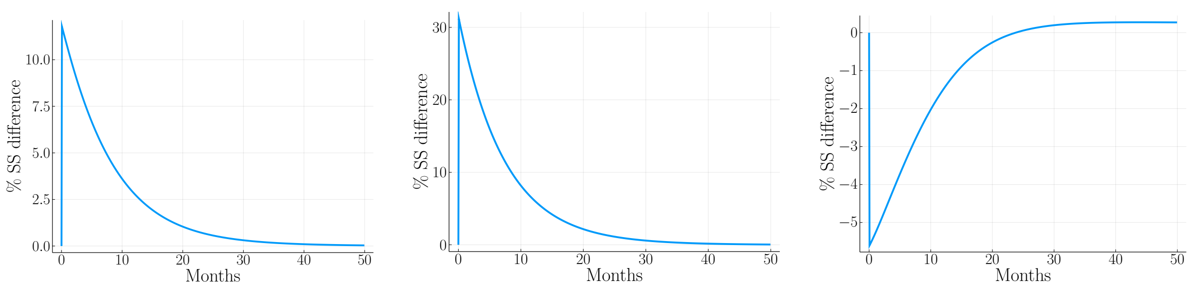
Notes: Panels A and B show the time series response of aggregate log real wage and the vacancy-to-unemployment rate, respectively, in response to the unexpected price level increase. Panel C shows the dynamics of the Beveridge curve in response to the same shock.

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. In other words, it is not

[30] In this counterfactual, endogenous layoffs fall upon impact as everyone's markdown falls by 13.5% as seen in Figure 5.1 moving workers away from the layoff margin. The endogenous layoff rate gradually returns to normal about three years after the shock.

puzzling at all through the lens of our model that real wages fall and vacancies increase during periods of unexpected inflation. 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.[31] With respect to this latter point, we show below that prior periods of inflation in the United States were associated with upward shifting Beveridge curves.

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



Panel A: Search Effort of Employed

Panel B: E-E Rate

Panel C: Starting Markdown of Job-Changers

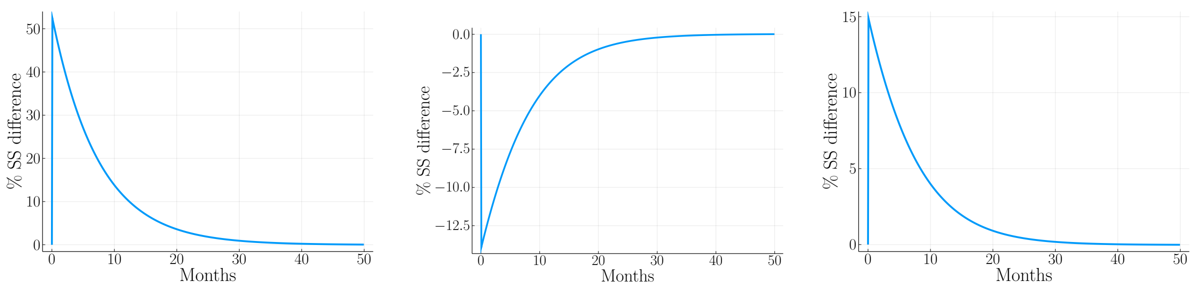
Notes: Figure shows the search effort the employed, the E-E rate, and the starting markdown of job-changers, respectively, in response to the one-time unexpected change in the price-level. All panels are reported as percent deviation from the steady-state.

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 to 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. Panels A to C show percentage differences from steady-state. Upon impact, the average workers' search

[31]The shifting Beveridge curve also highlights the difference between this model and benchmark sticky wage models such as the one in Galí (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.

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%. Our calibrated model is consistent with the survey findings in Stantcheva (2024) which report that about 10% of workers stated that the recent inflation caused them to switch to a higher paying job to escape their nominal wage decline.

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.

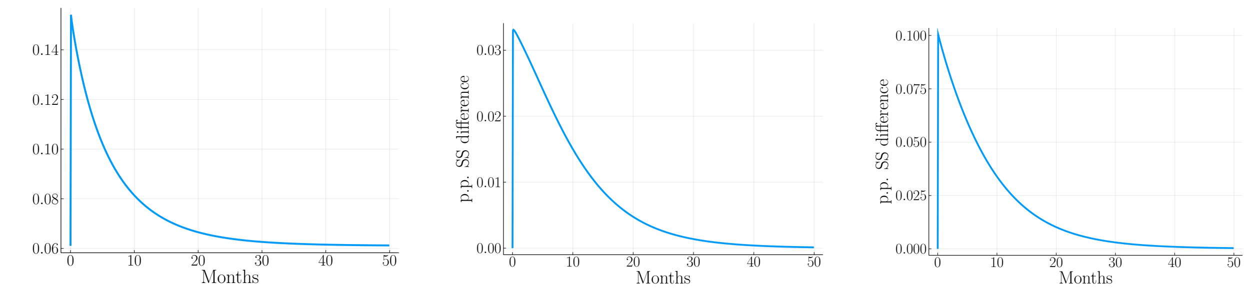
Figure 5.4 shows the response of vacancies created for workers making on-the-job transitions (Panel A), the E-E vacancy filling rate from the firm's perspective (Panel B) and the duration of E-E vacancies (Panel C). All figures show the percent deviation from steady-state. On impact, vacancies for E-E workers increase by 50% relative to their steady-state value.[32] As discussed in Section 3.1, the corresponding increase in vacancies associated with increasing E-E flows results in the firm's E-E job-filling rate falling and their E-E vacancy duration rate 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 that it was difficult to hire workers during late 2021 and 2022.[33]

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 cost to renegotiate their nominal wage with their employer. Panel A of Figure 5.5 shows that in response

[32]Total vacancies increase less than 50% because the vacancies created for U-E workers does not change much. The change in total vacancies is the weighted average of the change in vacancies for E-E workers and the change in vacancies for U-E workers.

[33]In the appendix, we follow the methodology in Davis, Faberman, and Haltiwanger (2013) to show that the duration of vacancies did, in fact, increase sharply during the inflation period.

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



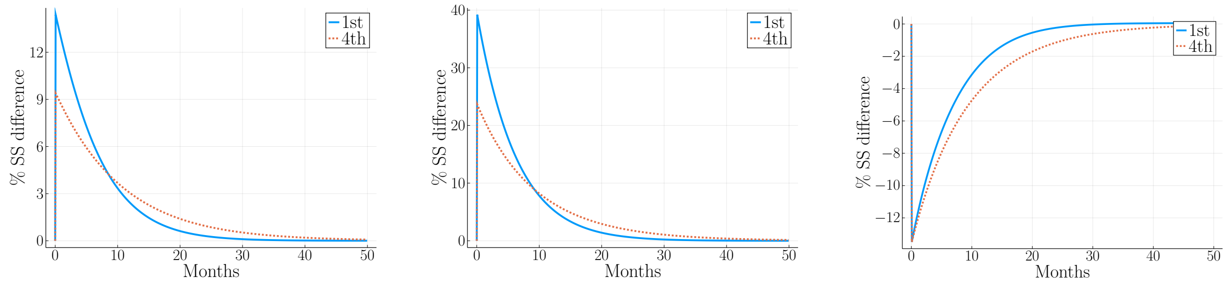
Panel A: Monthly Freq. of Wage Increases | Panel B: Wage Changes of Job Stayers | Panel C: Wage Changes of Job Changers

Notes: Panel A shows the times 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 the job stayers and job changers, respectively, in response to the same shock.

to inflation the frequency of wage increases for job-stayers jumped by 9 percentage points (from 6% per month to 15% per month). In addition, the average nominal wage change of job-stayers conditional on a change increased by about 3 percentage points in response to the inflation shock. Panel C also shows the analogous nominal wage change of job-changers in response to inflation. Similar to the APD data shown in Section 2, the nominal wages of job-changers increased by about 10 percentage points after the unexpected price level increase. As discussed above, the nominal wage change of job-changers increases by less than 13.5% because the job-changers are now searching in markets with larger wage markdowns on average (as shown in Panel C of Figure 5.3).

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. The reason for this is that we estimate that the lower productivity workers are more elastic to labor market shocks; in particular, we estimate that the cost of posting a vacancy for low-wage workers is lower than that of higher wage workers ($\phi^K > 1$). 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

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.

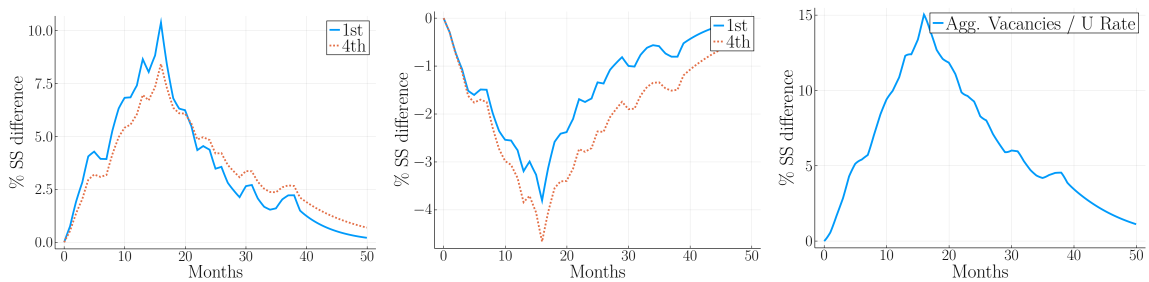
recover within two years, with most of the gain occurring in the first twelve months. The real wages of top quartile workers, however, take almost four years to fully recover. High-wage workers, therefore, have elevated on-the-job search—and subsequent E-E flows—for a much larger period of time than low-wage workers. After about one year, high-wage workers are searching and churning more than lower wage workers. This difference persists until the wages of both groups converge back to the steady-state path. 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.

5.2. Counterfactual 2: Series of Unexpected Price Level Shocks

In this subsection, we feed in a series of unexpected price level shocks over 40 months that match the price level changes in the U.S. data during the inflation period. As discussed above, when we assess the model predictions from this counterfactual, we need to take a stance on what workers and firms are expecting about the future path of inflation. For this analysis, we explore the extreme assumption that in each period the agents expected the trend growth in the price level (i.e., 2.2% per year) and they were continuously surprised by each subsequent price level shock. Such an assumption provides a lower bound estimate of how labor market flows responded during this period. If we incorporated expectations of future price-level changes, the magnitudes of the response of worker flows and vacancies would be larger as some of the adjustment would be front-loaded.

Figure 5.7 shows the response of E-E flows (Panel A), real wages (Panel B), and the

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 search effort among the employed (Panel A), E-E rates (Panel B), and wages (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 June 2024 period.

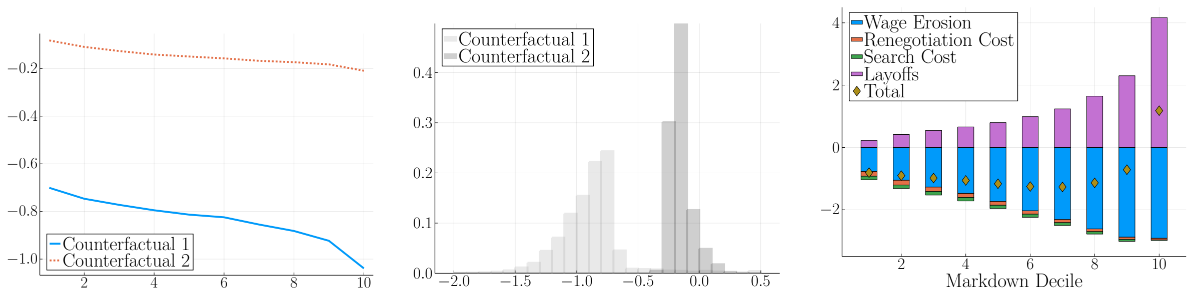
Vacancy-to-Unemployment ratio (Panel C) to the series of price level shocks. In Panels A and B, we show the response of workers in the top and bottom wage quartiles. The findings in Panels A and B are broadly consistent with the data. The E-E rate increases by about 8-10% for both low- and high-wage workers, while real wages fell by about 5 percent in mid-2022 for high-wage workers and about 4 percent for lower-wage workers. Wages rebounded more quickly for lower-wage workers, as in the data. The model predicts that the wages of high-wage workers are still below steady-state values even four years after the start of the inflation period. The vacancy-to-unemployment rate increases by about 15% with this counterfactual, which is smaller than what is observed in the data in part because, again, we are holding inflation expectations constant.

5.3. Worker Welfare

Both of the counterfactuals above show that a burst of unexpected inflation can generate patterns of worker flows and wage changes that are consistent with the data during this period. The one-time shock gives an upper bound on potential magnitudes, while the series of shocks (holding expectations constant) likely provides a more accurate assessment of actual welfare changes experienced by workers, which we now quantify.

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

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.

real wage to avoid the temporary increase in inflation. As seen from the figure, workers in all productivity deciles experience welfare losses by the unexpected increase in the price level under both counterfactuals, with higher-productivity workers consistently suffering larger 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 the recent inflation reduced the welfare of the median worker by about $1000. This is also a very sizeable number. Given 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.

To further put these losses into perspective, we conduct a third counterfactual analysis through the lens of the model. In particular, we ask how big would a job-destruction shock (implemented as an exogenous one-time aggregate increase in δ) have to be in order to generate the same average welfare losses from counterfactual 2. We find that the job-destruction rate would need to increase by approximately 3.1 percentage points in order to generate the same average welfare loss that resulted from the recent inflation. This suggests that the welfare loss from the inflation is akin to having a one-time shock that increases the unemployment rate above 7%. These results provide a model-based explanation for the survey results in Stantcheva (2024) showing that the vast majority of workers report disliking the current inflationary period.

Panel B reveals substantial heterogeneity in welfare losses underlying the patterns in Panel A. Consider the distribution of welfare losses from counterfactual 2 shown in the darker gray bars. Some workers lost over a 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 left 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 wage at other firms, (iii) workers have to incur renegotiation costs to increase their wage 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 of 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.

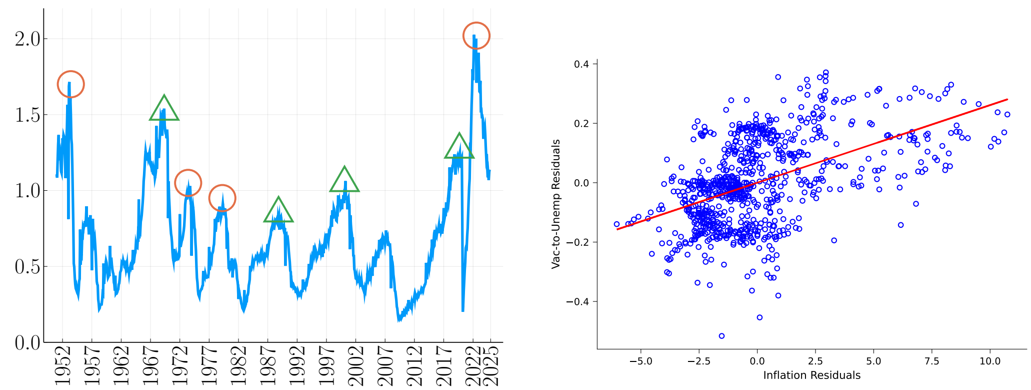
Consistent with our discussion above, the welfare gains from the reduced layoff margins are largest for workers with the highest initial markdowns (top decile). These are the workers who are closest to the layoff margin. The markdown deciles are drawn based on the ex-ante markdown before the inflation 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 non-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 also 20% of the total welfare loss for the median worker is attributed to increased search and renegotiation costs.

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

In the prior section, we documented that a burst of inflation by itself can cause a sharp increase in the vacancy-to-unemployment rate and an upward shift in the Beveridge curve during the 2021-2024 period, all else equal. In this section, 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 also show that these periods were also associated with a systematic rise in firm profits as predicted by our model.

Panel A of Figure 6.1 shows the monthly vacancy-to-unemployment rate in the U.S. between 1950 and 2024. 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 U.S. starting in 1951. For this figure, we divide the total number of monthly vacancies by the total number of unemployed individuals within the month as reported by the Bureau of Labor Statistics. The average vacancy-to-unemployment rate over the entire 1951-2024 period was approximately 0.7.

Figure 6.1: Vacancy to Unemployment Rate and Inflation Over Time



Panel A: V/U Rate 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 rate 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 rates against residualized monthly year-over-year inflation rates for the 1950 to 2019 period. The residuals are computed by regressing the variables on the unemployment rate and the unemployment rate squared.

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.[34] 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%. However, four of the other 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 was relatively constant (during the early 1950s and the 2021-2023 period); these periods, as we show below, are periods

[34] For example, the unemployment rate fell from about 7% to 4% between both the 1993-1999 period and the 2014-2019 period. The unemployment rate fell from about 6% to 3.5% during the 1964-1969 period and from about 7% to 5% during the 1986-1989 period.

when the Beveridge curve shifted upwards. Notice that the four periods denoted with the red circles are also periods where it has been shown that aggregate supply shocks were important drivers of the observed inflation.[35]

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 puts upward pressure on the vacancy-to-unemployment rate while at the same time 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.[36]

To formally show that high inflation rates can cause 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 curve. We also analyze whether inflation is associated with a rise in measured market tightness by showing how inflation affects the ratio of vacancies to unemployment conditional on the unemployment rate.

The results of estimating these regressions are reported in Table 4. Columns (1)-(3) show

[35] The inflationary period in 1950-1952 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.

[36] 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.

the results when the dependent variable is the vacancy rate; these regressions replicate the Beveridge curve estimates and explore whether inflation systematically shifts 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 results in an upward shift in the Beveridge curve by increasing vacancies conditional on unemployment (column (2)) and results in an increase in the V/U rate conditional on unemployment (column (5)). For example, the regression shows that an increase in the inflation rate by 10 percentage points increases the vacancy-to-unemployment rate by 0.23 percentage points. 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 (%)	-0.251	-0.289	-0.509	-0.152	-0.158	-0.531
	(0.016)	(0.013)	(0.079)	(0.004)	(0.003)	(0.016)
Unemp. Rate Sq.			0.017			0.030
			(0.006)			(0.001)
Inflation Rate (%)		0.142	0.144		0.023	0.026
		(0.008)	(0.008)		(0.002)	(0.001)
R^2	0.24	0.46	0.46	0.67	0.72	0.83

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 by 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 period. 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 Online Appendix Table B.3 and Appendix Figure B.12, 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 during the last 75 years.

7 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 the literature has identified as the potential cause of the recent inflation.

7.1. 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. In particular, 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 22.5%. 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 5: 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	22.5	22.7	22.1	22.7	23.3
% Δ EE Rate	31.2	20.9	8.2	11.4	6.8
% Δ UE Rate	-0.0	6.4	13.7	10.5	15.1
% Δ Layoff Rate	-100.0	-97.8	-19.4	58.8	-13.9
p.p. Δ Avg. Real Wage over 12 months	-3.2	4.7	-1.0	0.1	-1.4
p.p. Δ Avg. Real Wage Growth (Stayers)	3.3	1.1	-0.0	-0.0	-0.0
p.p. Δ Avg. Real Wage Growth (Switchers)	10.0	4.8	-0.3	-0.3	-0.6

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. 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 5. The positive productivity shock provides the closest approximation to the empirical data, with two notable exceptions. First, the productivity shock generates large real wages 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.

7.2. 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 (2023b) 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 coming 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 5). 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 rising 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.

8 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 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. Our conservative estimate finds that the average worker cumulatively lost approximately one-fifth of one month's consumption stemming from the 2021-2023 inflation, equivalent to about $1000 for the average worker. These welfare losses are substantial, comparable to those stemming from a 3.1 percentage point increase in the exogenous job separation rate that would generate an aggregate unemployment rate exceeding 7%. Most of the welfare loss stems from the real wage declines given 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 also 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, Mann, Sahin, and Violante (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.

References

Afrouzi, H., A. Dietrich, K. Myrseth, R. Priftis, and R. Schoenle (2024): "Inflation preferences," Discussion paper, National Bureau of Economic Research.

Alvarez, F., H. Le Bihan, and F. Lippi (2016): "The Real Effects of Monetary Shocks in Sticky Price Models: A Sufficient Statistic Approach," *American Economic Review*, 106(10), 2817–51.

Alves, F., and G. L. Violante (2023): "Some Like It Hot: Monetary Policy Under Okun's Hypothesis," Manuscript.

Autor, D., A. Dube, and A. McGrew (2024): "The Unexpected Compression: Competition at Work in the Low Wage Labor Market," Working Paper 31010, National Bureau of Economic Research.

Bagga, S., L. Mann, A. Sahin, and G. Violante (2025): "Job Amenity Shocks and Labor Reallocation," Discussion paper, Working Paper.

Barnichon, R. (2010): "Building a composite Help-Wanted Index," *Economics Letters*, 109(3), 175–178.

Barro, R. J. (1972): "A theory of monopolistic price adjustment," *The Review of Economic Studies*, 39(1), 17–26.

Benigno, P., and G. B. Eggertsson (2023): "It's Baaack: The Surge in Inflation in the 2020s and the Return of the Non-Linear Phillips Curve," Working Paper 31197, National Bureau of Economic Research.

Bernanke, B., and O. Blanchard (2024): "What Caused the U.S. Pandemic Era Inflation?," *American Economic Journal: Macroeconomics*.

Bils, M., M. Kudlyak, and P. Lins (2023): "The Quality-Adjusted Cyclical Price of Labor," *Journal of Labor Economics*, 41(S1), S13–S59.

Blanco, A., A. Drenik, C. Moser, and E. Zaratiegui (2024): "A Theory of Labor Markets with Inefficient Turnover," Working Paper 32409, National Bureau of Economic Research.

Chan, M., E. Mattana, S. Salgado, and M. Xu (2023): "Wage Setting and Passthrough: The Role of Market Power, Production Technology and Adjustment Costs," Discussion paper, Working Paper.

Cheremukhin, A., and P. Restrepo-Echavarria (2023): "The Dual Beveridge Curve," Manuscript.

Chodorow-Reich, G., and L. Karabarbounis (2016a): "The Cyclicality of the Opportunity Cost of Employment," *Journal of Political Economy*, 124(6), 1563–1618.

——— (2016b): "The cyclicality of the opportunity cost of employment," *Journal of Political Economy*, 124(6), 1563–1618.

Davis, S. J., R. J. Faberman, and J. C. Haltiwanger (2013): "The establishment-level behavior of vacancies and hiring," *The Quarterly Journal of Economics*, 128(2), 581–622.

Durante, A., J. Larrimore, C. Park, and A. Tranfaglia (2017): "Report on the economic well-being of us households in 2016," Discussion paper, Board of Governors of the Federal Reserve System (US).

Ellieroth, K., and A. Michaud (2024): "Quits, Layoffs, and Labor Supply," Opportunity and Inclusive Growth Institute Working Paper #94.

Fujita, S., G. Moscarini, and F. Postel-Vinay (2024): "Measuring Employer-to-Employer Reallocation," *American Economic Journal: Macroeconomics*, 16(3), 1–51.

Galí, J. (2015): *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*. Princeton University Press.

Gertler, M., C. Huckfeldt, and A. Trigari (2020): "Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires," *The Review of Economic Studies*, 87(4), 1876–1914.

Grigsby, J., E. Hurst, and A. Yildirmaz (2021): "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data," *American Economic Review*, 111(2), 428–71.

Guerreiro, J., J. Hazell, C. Lian, and C. Patterson (2024): "Why Do Workers Dislike Inflation? Wage Erosion and Conflict Costs," Discussion paper, Working Paper.

Hajdini, I., E. S. Knotek, J. Leer, M. Pedemonte, R. W. Rich, and R. Schoenle (2022): "Low Passthrough from Inflation Expectations to Income Growth Expectations: Why People Dislike Inflation," Working papers, Federal Reserve Bank of Cleveland.

Hall, R. E. (2017): "High discounts and high unemployment," *American Economic Review*, 107(2), 305–330.

HAZELL, J., AND B. TASKA (2024): "Downward Rigidity in the Wage for New Hires," *American Economic Review*, forthcoming.

HOSIOS, A. J. (1990): "On the efficiency of matching and related models of search and unemployment," *The Review of Economic Studies*, 57(2), 279–298.

HYATT, H. R. (2015): "The decline in job-to-job flows," *IZA World of Labor*, pp. 175–175.

JAROSCH, G. (2023): "Searching for job security and the consequences of job loss," *Econometrica*, 91(3), 903–942.

KUDLYAK, M. (2014): "The cyclicality of the user cost of labor," *Journal of Monetary Economics*, 68, 53–67.

KUSHNER, H. J., AND P. DUPUIS (2001): *Finite Time Problems and Nonlinear Filtering*pp. 325–345. Springer New York, New York, NY.

LORENZONI, G., AND I. WERNING (2023a): "Inflation is Conflict," Manuscript.

——— (2023b): "Wage-Price Spirals," *Brookings Papers on Economic Activity*, Fall.

MOSCARINI, G., AND F. POSTEL-VINAY (2023): "The Job Ladder: Inflation vs. Reallocation," Working Paper 31466, National Bureau of Economic Research.

NAKAMURA, E., AND J. STEINSSON (2010): "Monetary non-neutrality in a multisector menu cost model," *The Quarterly journal of economics*, 125(3), 961–1013.

PETRONGOLO, B., AND C. A. PISSARIDES (2001): "Looking into the black box: A survey of the matching function," *Journal of Economic literature*, 39(2), 390–431.

PHELAN, T., AND K. ESLAMI (2022): "Applications of Markov chain approximation methods to optimal control problems in economics," *Journal of Economic Dynamics and Control*, 143, 104437.

PILOSSOPH, L., AND J. RYNGAERT (2023): "Job Search, Wages, and Inflation," Discussion paper, Working Paper.

PILOSSOPH, L., J. RYNGAERT, AND J. WEDEWER (2024): "The Search Costs of Inflation," Discussion paper, Mimeo-Duke University.

REED, S. B. (2014): "One hundred years of price change: the Consumer Price Index and the American Inflation Experience," *Monthly Labor Review*, U.S. Bureau of Labor Statistics.

SHESHINSKI, E., AND Y. WEISS (1977): "Inflation and costs of price adjustment," *The Review of Economic Studies*, 44(2), 287–303.

SHILLER, R. (1997): "Why Do People Dislike Inflation?," in *Reducing Inflation: Motivation and Strategy*. University of Chicago Press.

SHIMER, R. (2012): "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 15(2), 127–148.

STANTCHEVA, S. (2024): "Why Do We Dislike Inflation?," *Brookings Papers on Economic Activity*, Spring.

VOLPE, O. (2024): "Job Preferences, Labor Market Power, and Inequality," Discussion paper, Working Paper.

Online Appendix

"A Theory of How Workers Keep Up With Inflation"

Afrouzi, Blanco, Drenik, and Hurst

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 this 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 January 2016 through the December 2024 period. We downloaded the data directly from the JOLTS data website.[37] The JOLTS dataset, collected by the U.S. Bureau of Labor Statistics (BLS) provides a snapshot of worker hiring and separation flows for a nationally representative sample of non-farm business and government employers during a given month. Below, we provide definitions of the JOLTS Layoff Rate, Quit Rate, and Vacancy Rate.

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

Quit Rate: The *quit rate* reflects workers who left voluntarily during the month divided by total employment at the end of the month. The quit rate captures workers who left the firm by either (i) flowing into unemployment before starting to look for another job (a voluntary "E-U" flow), (ii) directly transitioning to another firm (an "E-E" flow), or (iii) leaving the labor force (an "E-N" flow).

Vacancy Rate: The *vacancy rate* (or job-opening rate) is the number of open positions on the last business day of the month divided by the sum of employment and vacancies on the last day of the month. This data was also used when making the vacancy-to-unemployment rate series shown in Panel A of Figure 1.1.

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

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*.[38] The Wage Tracker Index uses the panel component of the *Current Population Survey (CPS)* to make a measure of composition adjusted nominal wage growth. The structure of the CPS is such that individuals are in the sample for four months where they are surveyed about their labor market activities. After that, they leave the sample for eight months and then re-enter for a final four additional months. In their fourth survey month and their eight survey month - which takes place one year apart - individuals are asked about their wages. The Atlanta Fed Wage tracker measures a year-over-year change in the workers per-hour nominal wage on their main job. For 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 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 with 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 take 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 and show that nearly all groups are below their trend wages even at the end of 2024.

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).

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

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) who extracted the series from *Current Population Survey*. We downloaded the series "Infa-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 use 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 make 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) who extracted the series from *Current Population Survey* aggregates published by the BLS to make the U-E rate. We divide the former by the latter and then take a three month moving average to make the monthly E-U rate. The two series can be found at https://fred.stlouisfed.org/series/LNS17400000 and https://fred.stlouisfed.org/series/UNEMPLOY, respectively.

E-U Flows: To make 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) who extracted the series from *Current Population Survey* aggregates published by the BLS to make the E-U rate. We divide the former by the latter and then take a three month moving average to make 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 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 graduate+. 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-Unemployemnt (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 workers 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 drop all respondents who have hourly earnings of less than \$2.13 and 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 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 true E-E flows, so we use a constant scaling factor to scale our E-E flows by deciles to hit the aggregate E-E rate as calculated by Fujita, Moscarini, and Postel-Vinay (2024). The decision of a constant scaling factor across deciles warrants discussion. If the elasticity of E-E probability varies with earnings then the scaling factor should be different. According to our model, returns to search effort, in expectations, 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 is 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 the 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 component so that we fit the aggregate E-U rate.

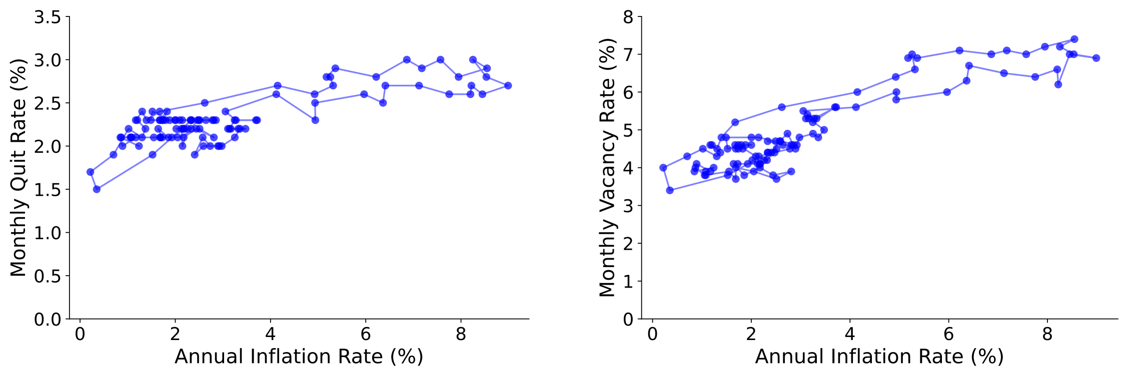
B Additional Descriptive Results

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 2016-2014 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.

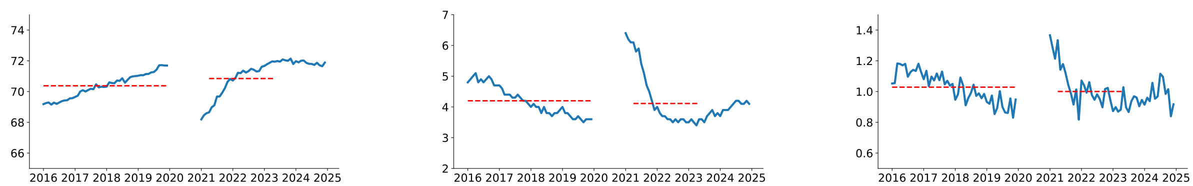
Likewise, as seen from Panel B of Appendix Figure B.1, there is also a tight relationship between the year-over-year CPI inflation rate and the monthly vacancy rate. This figure is analogous to the Beveridge curve but with the price inflation rate on the x-axis instead of the unemployment rate. While 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 and B of Figure B.2 show the employment to population ratio and the unemployment 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 (Jan 2016 through Dec 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 rate was 4.2 and 4.1, respectively, during the pre-period and inflation period. Both the decline in the EPOP rate and the increase in the unemployment rate during the pandemic completely recovered to pre-pandemic levels by the fall of 2021.

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



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

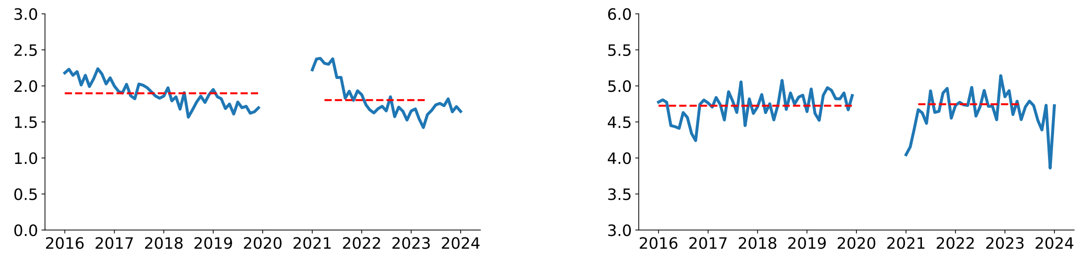
Notes: Figure shows the monthly employment-to-population ratio for 15–64 year olds (Panel A), the unemployment rate (Panel B), and the E-U rate (Panel C) during the 2016–2024 period in the United States. Data is from the St. Louis Federal Reserve Economic Database (FRED). For readability, we exclude the data from 2020 which featured several months of double digit unemployment and catering employment to population ratios, and high E-U rate for the initial covid-19 shock.

Appendix Table B.1 shows the average employment rate for different demographic groups in both the January 2016 to December 2019 pre-period and then again for the April 2021 to May 2023 inflation period. As seen from the table, the employment rate was essentially unchanged between the periods for the four demographic groups.[39] Collectively, these results show that the recent inflation period was not associated with either substantively increasing employment rates nor with substantive changes in unemployment rates relative to the pre-pandemic period.

Panel C of Appendix Figure B.2 show the time series pattern of E-U rates during the 2016-2024 period. For readability, we exclude the data from April 2020 from the graph when

[39]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.

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 average. The data series taken directly from FRED.

Table B.1: Employment to Population Ratio Over Time, 25-55 Year Olds

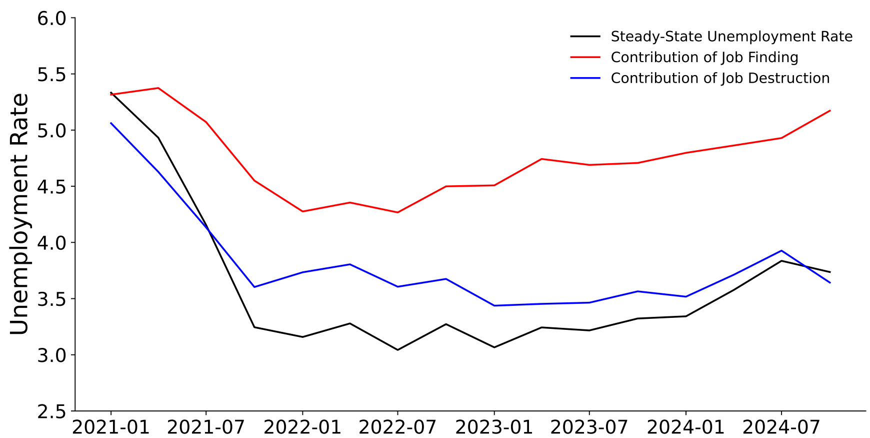
Education	2016M1-2019M12	2021M4-2023M5
Men: Less than Bachelors	0.820	0.810
Men: Bachelors or More	0.920	0.918
Women: Less than Bachelors	0.664	0.660
Women: Bachelors or More	0.814	0.826
All	0.788	0.792

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. Column 1 shows the average employment rate during the January 2016 to December 2019 pre-period while Column 2 shows the average employment rate during the April 2021 to May 2023 inflation period. The sample focuses on those aged 25-55 from the monthly CPS files.

the E-U rate exceeded 13%. As seen from the figure, the E-U rate did not change at all during the inflation period relative to the pre-period. This implies that all of the documented quits from the JOLTS data are showing up as increased E-E churn.

Finally, Appendix Figure B.4 shows that the decline of unemployment between January 2021 and September of 2021 coming out of the pandemic (black line) was largely driven by declining job destruction rate (or layoffs, black line) rather than 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 job destruction rate closely track the dynamics of unemployment during this period. This is a unique feature of labor market flows during the $2021-2024$ inflation period as Shimer (2012) finds that job-finding (rather than job-destruction) explains 80% of the variation in unemployment since 1948 in the US data. These results are consistent with the fact that the U-E rate did not change much during the inflation period; instead it was the decline in layoffs that were driving unemployment dynamics.

Figure B.4: Decomposition of Unemployment Dynamics

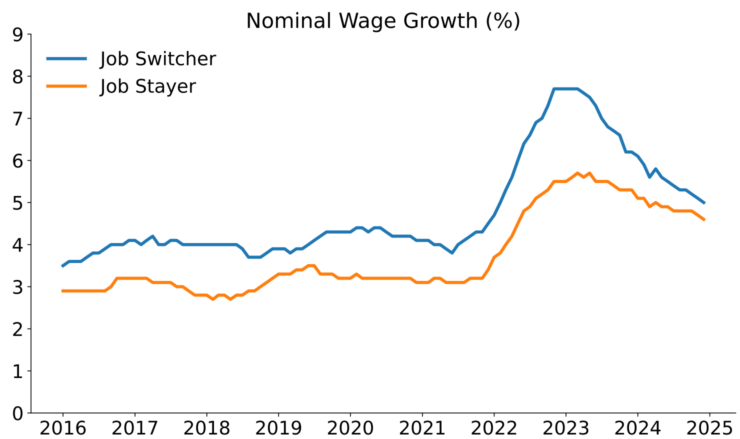


Notes: Contribution of fluctuations in the job finding (U-E) and job destruction (E-U) rates to fluctuation in the unemployment rate, 2021-2024, quarterly average of monthly data. The red line shows the counterfactual unemployment rate if all fluctuation were due to changes in the job finding rate ($\frac{\bar{\delta}}{\bar{\delta}+\lambda_t}$) 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 $1990-2024$.

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. As discussed above, the underlying data for the *Atlanta Fed Wage Tracker* comes from the *CPS*. A key limitation of using the *CPS* data to measure the wage growth of job-changers is that the CPS follows addresses not people. If someone moves addresses they drop out of the *CPS*. Job-changers - particularly those that get large wage increases - are more likely to move locations than job-stayers. So, the *CPS* data may be downward biased for the wage growth of job-changers because the data does not capture the large wage changes of job-changers who move. None-the-less, the patterns in the Atlanta Fed data are broadly similar to what we show in the main paper using ADP data. In particular, as seen in Appendix Figure B.5, the gap in wage growth between job-changers and job-stayers doubled during the inflation period–just like the doubling observed in the ADP data. However, relative to the ADP data, the wage growth of job-changers relative to job-stayers is smaller in levels both during the pre-period and the inflation period consistent with the fact that the CPS may be missing some of the big wage changes of job-changers who also change residences.[40]

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



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

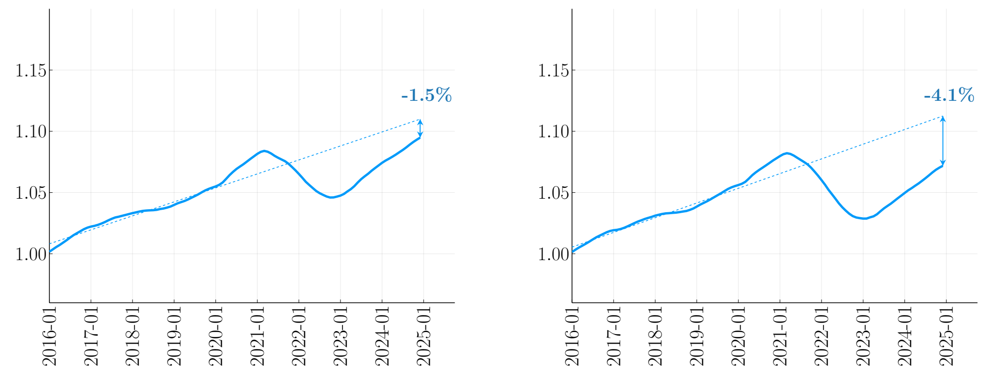
B.4. Additional Wages Dynamics During the Inflation Period

In this subsection, we show additional data on nominal wage growth throughout the wage distribution during the inflation period. To start, Figure B.6 shows the nominal wage growth for quartiles 2 and 3 during the 2016-2024 period. These figures are analogous to what was shown for quartiles 1 and 4 in the main text.

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

[40]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.

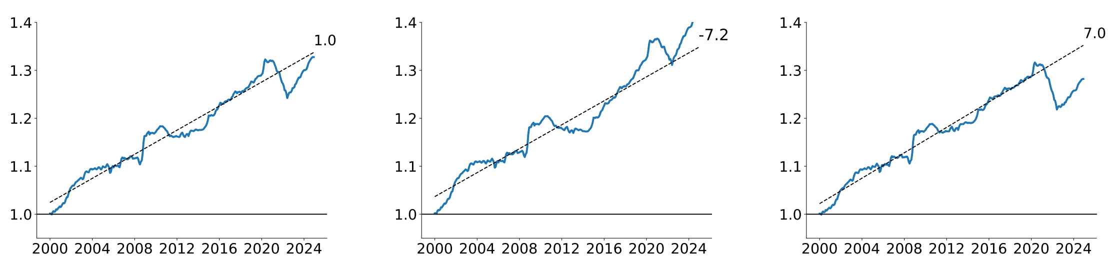
Figure B.6: Real Wage Growth, By Wage Quartile



Panel A: 2nd Income Quartile Panel B: 3rd Income 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 shows the 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.

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



Panel A: Median Panel B: Bottom Quartile Panel C: Top Quartile

Notes: This figure shows the evolution of real wages across the income distribution between 2000 and 2024 for the same the median worker (Panel A), bottom quartile worker (Panel B) and top quartile worker (Panel C). The blue line indicates realized real wages and the dotted black line shows the trend in real wage. The trend in wages is recovered separately for each group on wage data between $2000-2019$. We project this trend on $2020-2024$ data to create a counterfactual wage gap between predicted and observed real wage for each income group in June of 2024. The data is directly taken from Atlanta Fed Wage tracker.

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 longer 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.

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

The first four columns of Appendix Table B.2 uses 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 Jan 2016 - Dec 2019 data) and the the inflation period (average over the monthly April 2021 - May 2023 data). For example, hires increased by 15% 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 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.

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

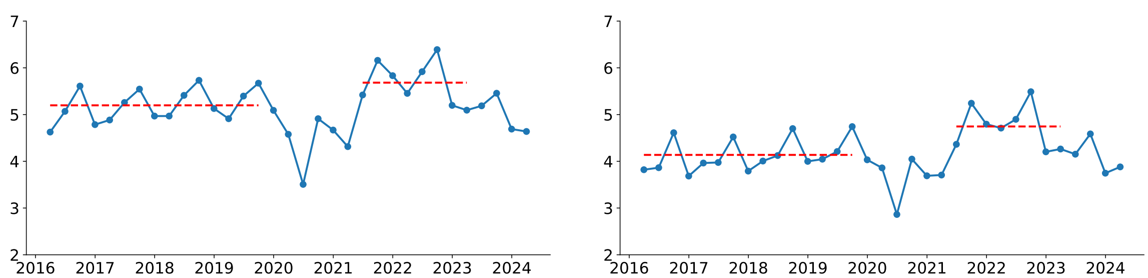
In this subsection, we use data from the LEHD to make a measure of E-E flows for people who graduated high school but had no college attendance (HS Graduates) and for individuals that graduated college (College Graduates+). The LEHD does not measure job-to-job flows by income groups so we use education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

Table B.2: Sectoral Labor Market Flows and Wages During Inflation Period

Industry	**Hires**	**% Change in** **Openings**	**Layoffs**	**Quits**	**Real Wage Gap**
Construction and Mining	-10	50	-34	-1	-1
Education and Health	15	76	-29	23	-4
Finance and Business Services	9	47	-18	18	-3
Leisure and Hospitality	10	64	-21	18	-3
Manufacturing	37	94	-3	55	-4
Trade and Transportation	12	60	-25	25	-4

Note: 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 period is measured as the industry-specific % difference between trend and realized real wages in December 2024.

Figure B.8: E-E Rates, By Education



PANEL A: HS GRADUATES

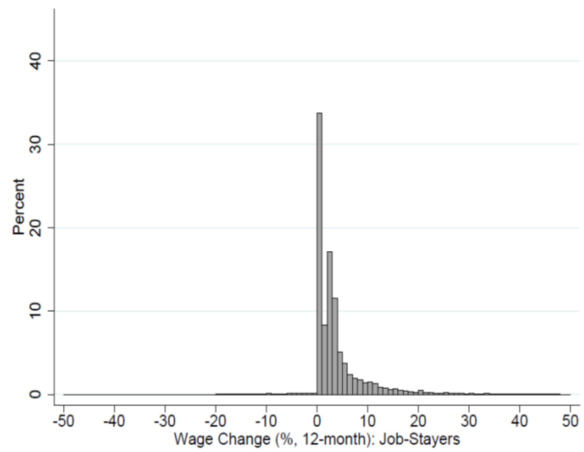
PANEL B: COLLEGE GRADUATES+

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.9 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 workers paid hourly and workers who are salaried. 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 of the sample and wage measures.

Figure B.9: 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.

B.8. Vacancy Duration During the Inflation Period

B.10 shows that the average time to fill a vacancy rose from about 30 days in the pre-period to 45 days during the peak of inflation. We use data on hires and vacancies at a monthly frequency from JOLTS to estimate the job-filling rate and back out the expected duration to fill a vacancy. Following the methodology described in Davis, Faberman, and Haltiwanger (2013), we assume that hires on day s of month t is given by:

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

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

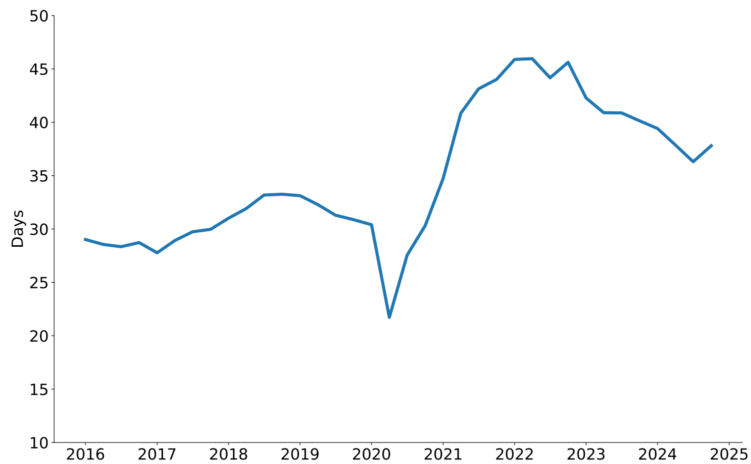
$$f = \frac{H}{v}\left(\frac{1}{\tau}\right) \tag{B.2}$$

$\tau = 26$ represents the number of working days in a month. Given monthly data on hires and vacancies, the job-filling rate f_t can be directly estimated. The duration of a vacancy, in expectation, is given by $\frac{1}{f_t}$, the object of B.10.

B.9. Corporate Profits Over Time and During the Inflation Period

Panel A of Appendix Figure B.11 shows the corporate profit to GDP ratio in the United States between 2016 and 2024 (quarterly). We downloaded this data directly from the FRED

Figure B.10: Duration of Vacancy

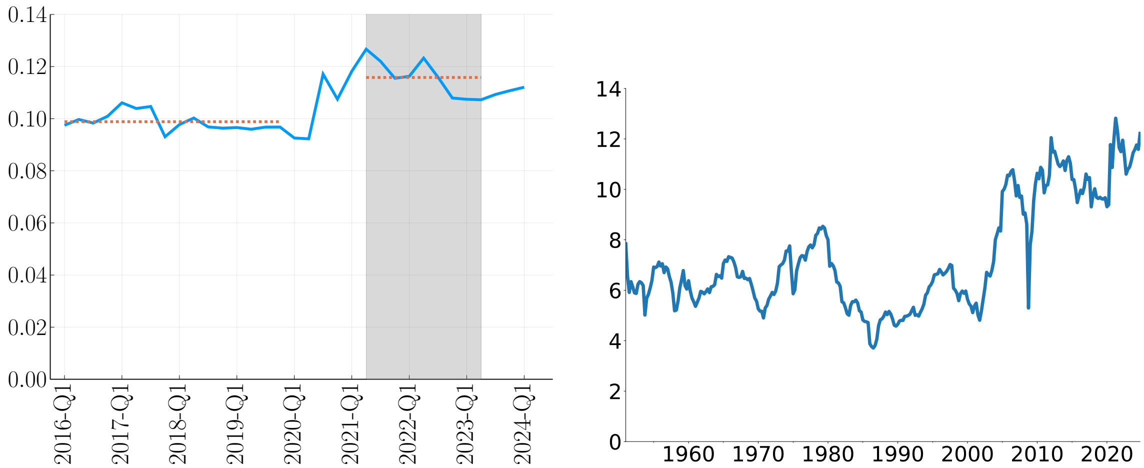


Notes: We estimate the job-filling rate given the data on the flow of hires and the stock of vacancies (see Davis, Faberman, and Haltiwanger (2013) for details). We take a quarterly average of the monthly job-filling rate and plot plot the implied duration of a vacancy.

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 where the corporate profit to GDP ratio exceeded 11% and there were no quarters where the ratio exceeded 12%. The current corporate profit to GDP ratio is at historically high levels. The rise in the corporate profit to GDP ratio is consistent with the prediction of our model where firm labor market power increased during the inflationary period because nominal wages are sticky. The rise in the corporate profit to GDP ratio at face value is inconsistent with other theories suggesting firm labor market power decreased during the post-pandemic period due to the labor market being tight.

It should be noted that the corporate profit to GDP ratio was also at historically high levels in 1950, 1974, and 1979 – all periods where the both the inflation rate was high and the labor market was not particularly strong. Specifically, between 1950 and 2000, there were only four periods when the corporate profit to GDP ratio exceeded 7%; three of those were the early 1950s, 1974, and 1979. Appendix Table B.3 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

Figure B.11: Quarterly Corporate Profits to GDP Ratio



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

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

during periods of inflation even controlling for the level of the unemployment rate. Appendix Figure B.12 plots quarterly profit share residuals against quarterly inflation residuals. We make 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.

C A Brief Overview of the Computational Algorithm

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

C.1. Smoothing Layoff and Quit Margins

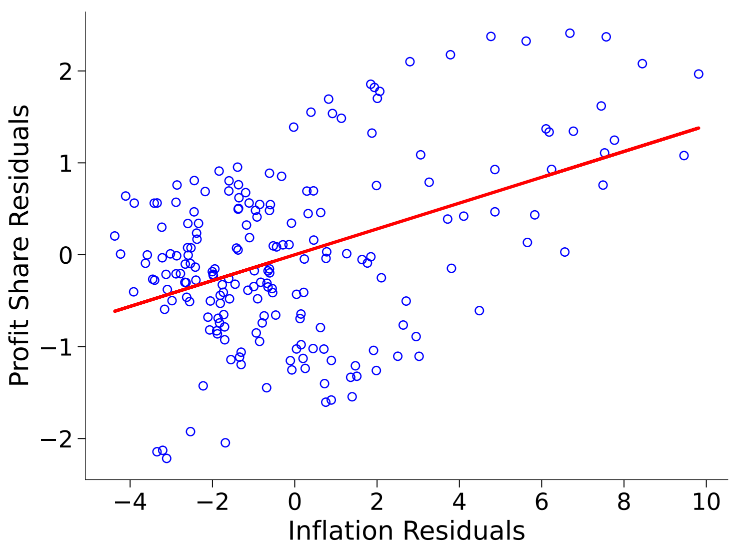
Without separation costs, a change in the quit and layoff thresholds generate a discrete change in the value of the firm and worker, respectively. As a result, the smooth-pasting conditions that usually applies at these thresholds do not hold. The discrete change in the value of each agent introduces 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

Table B.3: 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

Figure B.12: 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

type Z. Here, ν_t^h and ν_t^j respectively follow a compounded Poisson process such that, with probability $1 - \iota\, dt$, the quitting cost to the worker is $\bar{\nu}^h$ and likewise with probability $1 - \iota\, dt$ the firing cost is $\bar{\nu}^j$ to the firm. With probability $\iota\, dt$, 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:

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

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

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

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 $\partial_w J(z, w_l(z)) = 0$.

C.2. Algorithm Summary

C.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 to 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**: Continues iterations until value functions converge within specified tolerance levels.

C.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 mirroring 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.