Nominal Wage Adjustments during High Inflation and Tight Labor Markets

Maximiliano Dvorkin and Cassie Marks

Abstract

The U.S. economic recovery after COVID has been characterized by relatively high inflation and low unemployment. At the same time, average wages increased at a rapid pace during this period, faster than in previous years. Grigsby, Hurst, and Yildirmaz (2021) study nominal wage rigidity in the United States and document that before the pandemic, wage declines were rare and over 35 percent of workers would not receive a wage increase year over year. Given the larger-than-usual aggregate wage growth in the aftermath of the pandemic, we revisit these results and study the frequency and the magnitude of individual wage changes in a context of high inflation and tight labor markets. We find that individual wages increased more frequently and by a larger amount post-2021, but the pace and frequency of the increases moderated somewhat in 2023 compared to the previous year.

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1. INTRODUCTION

In an influential recent article, Grigsby, Hurst, and Yildirmaz (2021) study nominal wage rigidity in the United States, using administrative microdata from a large payroll processing company. They document that for the pre-pandemic years, wage declines were rare and over 35 percent of workers did not receive a wage increase year over year.

The U.S. economy in the aftermath of the COVID-19 pandemic has been characterized by high levels of inflation and low levels of unemployment. At the same time, average wages increased at a rapid pace during this period, faster than in previous years. Figure 1 plots the evolution of the monthly consumer price index (CPI) and the average hourly earnings for private workers from 2016 to the present, with the series indexed to January 2020 being equal to 100. Between January 2020 and December 2023, wages grew at a rate of 4.8 percent per year, while consumer prices grew at 4.5 percent, on average. In contrast, between January 2016 and December 2019, they grew at 2.8 percent and 2.1 percent, respectively. Thus, both average wages and inflation increased at a faster pace since 2020.

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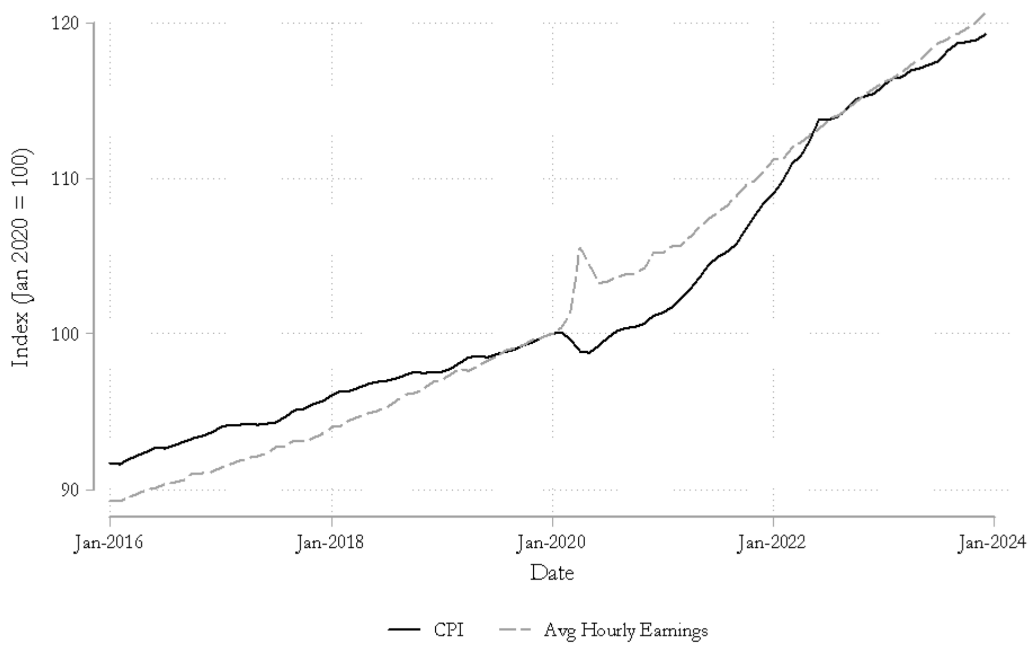
Figure 1
CPI and Average Hourly Wages



NOTE: Average hourly wages are for private workers.

The pace of aggregate wage changes since 2020 differs from the one observed before the pandemic. In this article, we study whether the frequency and the magnitude of wage changes at the individual level have also differed during these years of high inflation and tight labor markets. In other words, we study whether the documented nominal wage rigidities at the individual level change with economic conditions.

For this, we use microdata from Homebase, a private company that provides payroll, scheduling, and hours-tracking services to a large number of companies. After cleaning the data, our sample has over 70,000 U.S. establishments and 700,000 employees continuously employed for at least 12 months at the same company. The data have a high level of detail, with information on the number of hours worked, the location of employment, and the wage received by the worker.

Despite our sample's large size and the high frequency of observations, the Homebase data may not be representative of the distribution of employment in the U.S. economy. To address this concern, we start our analysis in Section 2 by comparing the Homebase sample with nationally representative data from surveys or administrative sources, such as the Quarterly Census of Employment and Wages (QCEW) and Current Employment Statistics (CES). We find that although the Homebase data are not perfectly representative of the U.S. labor market, they contain information on employment and wages for all 50 states and most industries. On the other hand, employment in some industries, such as food, drink, and leisure, is overrepresented in Homebase. Additionally, our sample does not include workers employed at firms with more than 500 employees and is skewed toward smaller businesses relative to the U.S. economy. While these are important differences between the *level* of employment in Homebase and the U.S. data, we show that Homebase is a reasonable source of information for tracking *changes* in aggregate and individual wages, as demonstrated in Dvorkin and Isaacson (2022).

We examine the evolution of wage changes from before the pandemic to the present day. We split our analysis into three time periods: 2018–19, 2022, and 2023. Overall, we find that both the frequency and the magnitude of individual wage changes are somewhat similar to those documented by Grigsby, Hurst, and Yildirmaz (2021) for the pre-pandemic years. However, wages increased more frequently and by a larger amount in 2022, when inflation was high. The pace and frequency of these increases moderated somewhat in 2023. This pattern provides evidence that the characteristics of nominal wage rigidities change when inflation is high.

Since the recent years were also characterized by tight labor markets and low unemployment, we revisit our analysis and examine the relationship between individual wage growth in periods of high inflation but controlling for the state of labor markets. For this, we use data on workers' geographic location and control for the unemployment level in their state during these periods. We find that while lower unemployment rates are associated with both larger month-over-month wage changes and a higher probability of wage changes, our previous findings stand: Wages change more frequently and by a larger amount in high-inflation years. Thus, wages change more and more frequently in high-inflation years, not just due to tight labor markets. This leads us to conclude that nominal wage rigidities are state dependent and influenced by the inflation level.

In this article, we extend the analysis in Dvorkin and Isaacson (2021) and Dvorkin and Isaacson (2022), which studies the pace of individual wage changes in the early months of the pandemic. We focus on analyzing the frequency and magnitude of wage changes in a period of high inflation and tight labor markets.

As previously mentioned, our study closely relates to Grigsby, Hurst, and Yildirmaz (2021). We take their study as a starting point and examine whether nominal wage rigidities differ in the aftermath of the pandemic. Our findings suggest that wages are somewhat more flexible (upwards) in periods of high inflation and low unemployment, as observed in recent years.

The rest of the article is organized as follows. In Section 2 we study the characteristics of the Homebase sample and compare it to nationally representative data sources in terms of employment and wage changes. In Section 3 we study different aspects of the distribution of nominal wage changes for job stayers in the Homebase data and describe the evolution of key moments of this distribution in the aftermath of the pandemic. In Section 4 we analyze the effects of labor market conditions and inflation on individual nominal wage changes. Finally, in Section 5 we conclude.

2. DATA DESCRIPTION

2.1 Overview of Homebase Data

Our main data source comes from Homebase microdata. Homebase is a private company providing payroll, scheduling, and hours-tracking software to over 100,000 businesses. The company offers both a free and premium version, attracting different types of businesses, especially small businesses. As we discuss later in detail, the majority of Homebase businesses are in the leisure and hospitality sector, particularly in the food and drink industry.

The microdata contain records of each shift worked by a worker at a Homebase business across the United States, with information on the number of hours worked, location of employment, and, in some cases, the wage the worker received. There is also a unique firm ID, location ID, and employee ID to help track individuals, establishments, and firms over time.

In most cases, Homebase also reports an average hourly wage for workers, which does not include tips but does include any extra overtime wages. Roughly 40 percent of workers in the data have some information on wages. Homebase updates its database daily, allowing us to see wage changes at a more granular level and with greater frequency.

After cleaning the data sample and imposing our selection criteria, our sample has close to 717,000 employees and 70,000 establishments.[1]

2.2 Representativeness of the Homebase Data

Homebase, although extensive, does not perfectly represent the characteristics of employment in the United States. In this section, we compare the Homebase data to two nationally representative data sources: the QCEW and the CES. We also compare our calculated wage growth to the Atlanta Fed's Wage Growth Tracker, which uses data from the Current Population Survey (CPS) on wages.

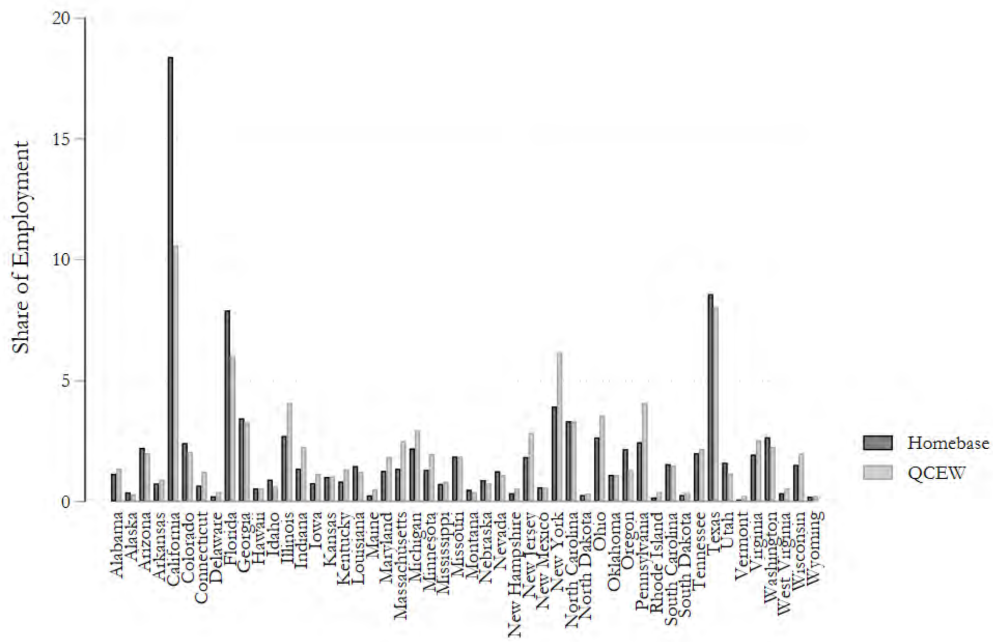
2.2.1 Quarterly Census of Employment and Wages

The QCEW is published quarterly by the Bureau of Labor Statistics (BLS). This dataset reports estimates of wages and employment levels for workers covered by state unemployment insurance laws and for federal workers covered by the Unemployment Compensation for Federal Employees program. The data are aggregated at the industry, firm size, and geographic level, and they cover 95 percent of U.S. employers. Since the QCEW is representative at the national and industry levels, it is helpful to compare it with the composition of Homebase. By and large, the Homebase data only include private employment. Therefore, we only compare the Homebase data with private employment in the QCEW.

Figure 2 compares the distributions of workers in the Homebase data and the QCEW across states. As the figure shows, all the Homebase data contains information on employment in all U.S. states and its distribution

1. In our sample, we keep workers continuously employed in the same firm for at least 12 months for those who have data on wages. Further, we remove from the sample individuals with an hourly wage below $5.

Figure 2
Distribution of Employment across States in Homebase and the United States



SOURCE: QCEW, Homebase, and authors' calculations.

closely resembles that in the QCEW data. However, employment in California, Texas, and Florida is overrepresented in the Homebase data, while New York, Illinois, and New Jersey are somewhat underrepresented relative to the QCEW data.

Looking at the distribution of employment by industry, Figure 3 shows that the food, drinks, and leisure sector accounts for a very large share of employment in the Homebase data, larger than in the QCEW data. In most other sectors, employment is underrepresented in the Homebase data, which is particularly noticeable in the financial services and information industry.

Next, looking at employment by firm size, Figure 4 shows that most of the employment in the Homebase data is in small establishments (less than 50 employees), while for the QCEW data, roughly 43 percent of people work in establishments with over 100 employees.

2.2.2 Current Employment Statistics

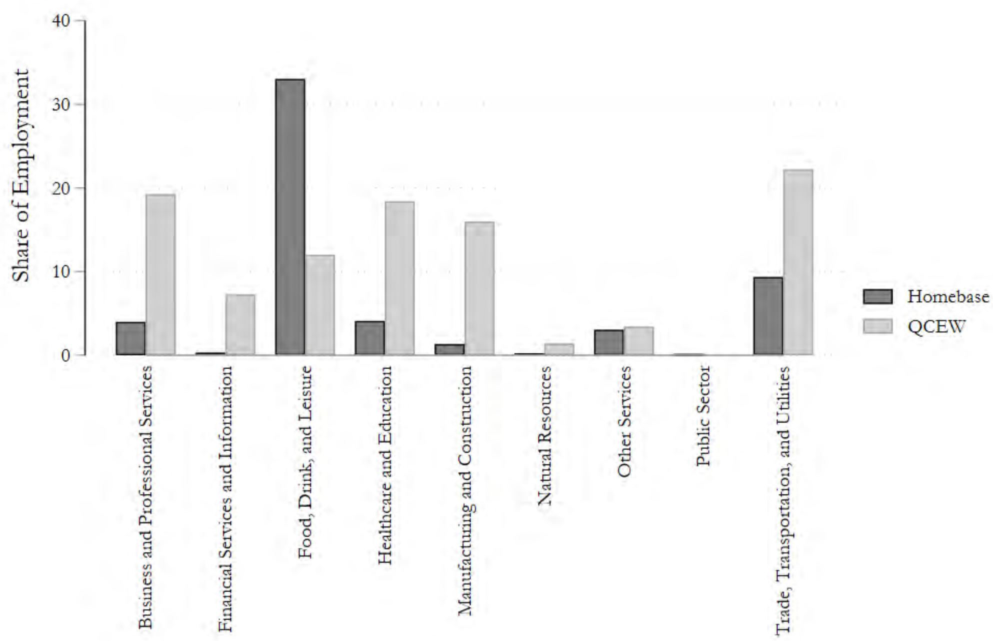
The CES, published monthly by the BLS, provides detailed industry estimates of nonfarm employment, hours, and earnings of workers on payrolls. The CES surveys approximately 122,000 businesses and government agencies, or approximately 666,000 individual worksites. The CES is a nationally representative database, making it a useful benchmark for evaluating the reported wages in the Homebase data.[2]

Figure 5 plots the average wage in Homebase and the average wage in the CES. Although the evolution of the two series is similar, the average wage level in Homebase is lower than the average wage in the CES. This difference could be for multiple reasons. First, Homebase is not perfectly representative of the U.S. labor force. In Homebase, industries with lower wages or wages supplemented with tips are overrepresented, such as employment in the food service industry. Homebase wages do not include tips, so actual take-home wages could be greater than reported wages. Second, Homebase is not perfectly representative of U.S. firms as it primarily consists of small firms (firms with 50 or fewer employees). Workers at smaller firms typically see lower wages than those at larger firms.

Although the level of wages differs, their changes over time in Homebase and the CES are highly correlated, indicating that information on wage inflation in Homebase could be informative of overall U.S. wage inflation. The second panel in Figure 5 plots the annualized monthly wage changes of Homebase and the BLS. Similar

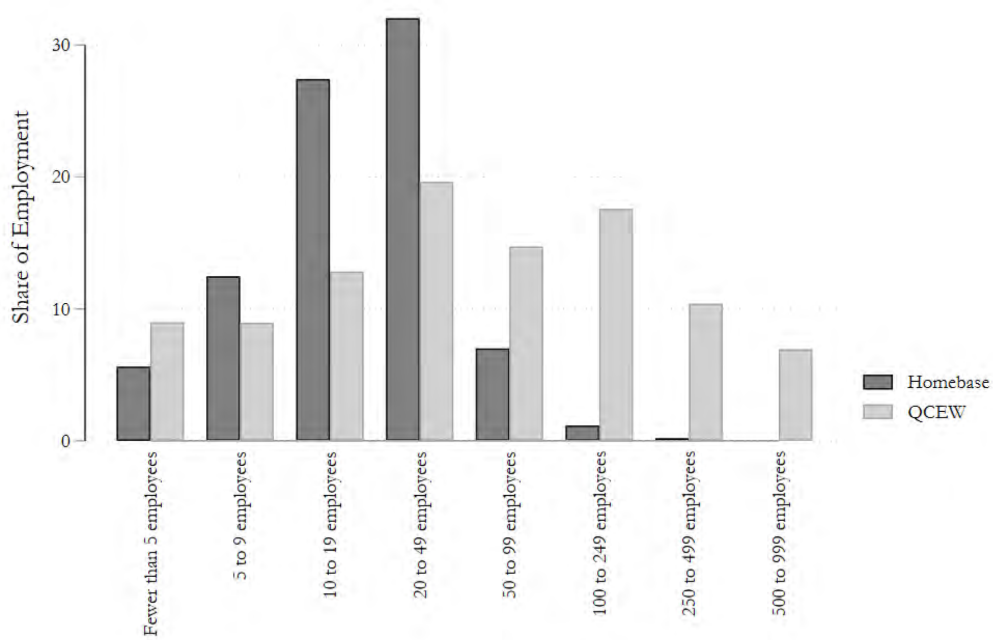
2. We use the wage data from the CES as they are available at the monthly frequency, as opposed to the QCEW where it is provided quarterly. This allows us to examine the evolution of wages at a higher frequency.

Figure 3
Distribution of Employment across Industries in Homebase and the United States



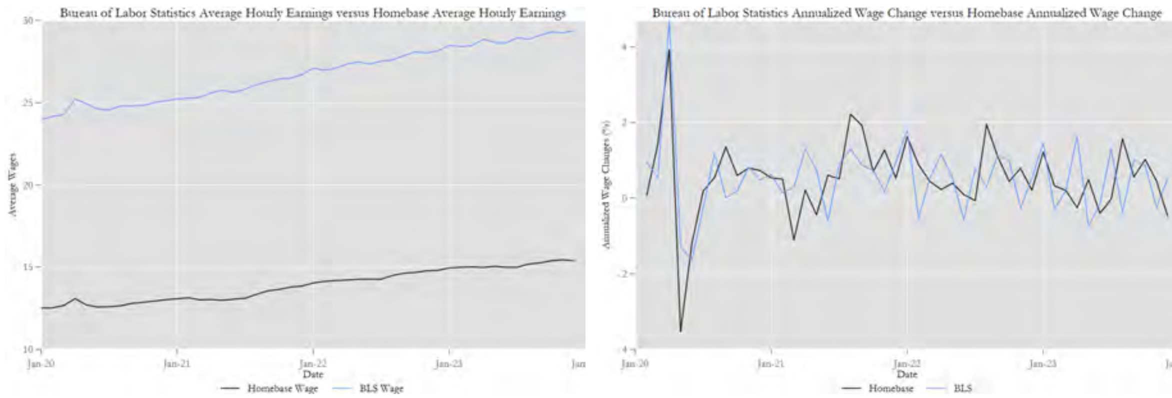
SOURCE: QCEW, Homebase, and authors' calculations.

Figure 4
Distribution of Employment across Establishment Size in Homebase and the United States



SOURCE: QCEW, Homebase, and authors' calculations.

Figure 5
Comparison of BLS and Homebase Wages and Wage Changes



SOURCE: CES, Homebase, and authors' calculations.

to the trend with the level of wages, the monthly changes tend to move together. Although Homebase is not a perfect match with the CES, it is strongly correlated. Due to Homebase's much higher frequency, this helps gauge economic conditions in real time.

2.2.3 Individual Wage Changes

In the previous subsection, we compared the evolution of average wages in the cross-section of workers in Homebase and the CES. Now, we examine the evolution of individual wage changes. To do this, we compute the wage changes for each individual in the Homebase data over a year and look at moments of the distribution of individual wage changes. After obtaining our measure, we compare it to similar measures reported in the Atlanta Fed's Wage Growth Tracker.

The Federal Reserve Bank of Atlanta maintains the Wage Growth Tracker, which is updated monthly. They use individual-level data from the CPS on reported pretax earnings. The Atlanta Fed then calculates the hourly wage by dividing usual weekly earnings by usual weekly hours, or actual hours if usual hours is missing. The Tracker excludes individuals who are self-employed, made more than $100,000 before 2003, make more than $150,000 after 2003, have missing earnings data, have hourly wages below $2.13 (the current federal minimum wage for tip-based workers), or are employed in agriculture. Approximately 2,000 individual wage growth observations are recorded each month. After matching the hourly earnings of individuals from any month to those from 12 months before, the Atlanta Fed reports the median wage change as a percentage.[3] In the next section we explain in detail our sample selection criteria to construct a measure of individual wage changes using the Homebase data. By and large, our sample selection criteria is similar to that of the Atlanta Fed in their construction of the Wage Growth Tracker.

Figure 6 compares the median of individual wage changes in Homebase with the Wage Growth Tracker for job stayers and hourly workers, respectively. As we will further explain in Section 3.1, Homebase panel data are by individual and company. In other words, we only compute wage changes for workers employed in the same company for a full year (job stayers).[4]

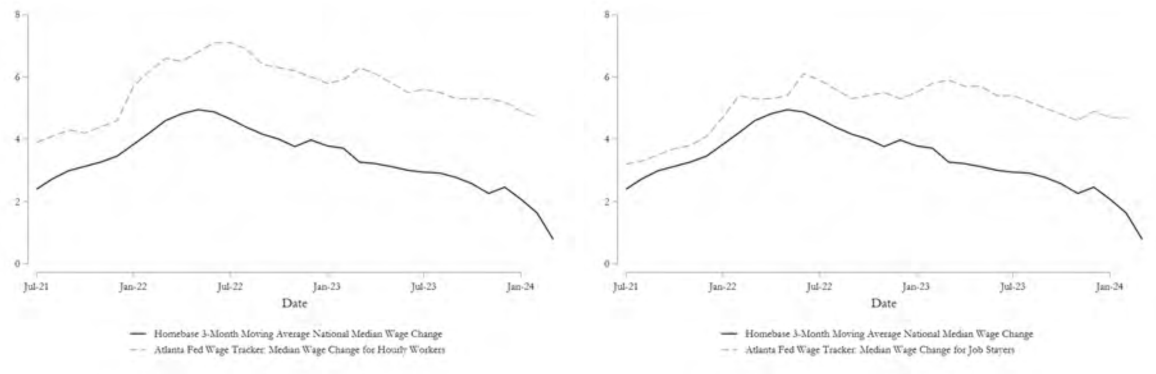
The magnitude of the median wage changes over a year is not the same across the two datasets. The gap between the median Homebase wage change and the Atlanta Fed median wage change varies over time, which may be driven by composition differences between the CPS and Homebase. In addition, note that in the CPS, wages over a year are not conditional on individuals continuously employed in the same firm for a full year, while for Homebase, they are. Since wages change more when workers switch employers, part of the differences in the wage changes may be driven by this difference in the calculations.

However, the evolution over time of the two series is highly correlated, suggesting that Homebase can be a useful tool for analyzing the evolution of wage changes. Since mid-2021, nominal wages in the U.S. increased at a very fast pace, as reflected in both series. By mid-2022, nominal wage inflation had peaked at a level roughly twice as large as that of early 2021 and started to moderate gradually. By the end of 2023, it had reached a level similar to those seen before the pandemic.

3. More information on their methodology is available on their website.

4. While the Atlanta Fed computes wage changes for job stayers, their definition of a job stayer differs because the CPS data do not allow us to distinguish whether a worker was employed at the same firm for a year.

Figure 6
Evolution of Percentage Change in Wages



SOURCE: The Federal Reserve Bank of Atlanta, Homebase, and authors' calculations.

3. NOMINAL WAGE ADJUSTMENTS FOR JOB STAYERS

Wages are an important component of production costs, and the evolution of wages may be informative of inflationary pressures. However, there are different ways to measure wage inflation. One way to measure it is to compute the changes over time in average hourly earnings for all private employees, as reported monthly by the BLS. We use this measure in Figure 5. According to this metric, wages increased 4 percent between November 2022 and November 2023. The issue with this measure is that changes in the workforce composition may significantly impact the measure of wage inflation. For example, if a large number of workers with low wages (below average) enter the sample, this would decrease the measure of wage growth, even if each worker's wages did not change.

Another way to measure wage inflation is by examining the change in the wages of individual workers from one period to the next, and then computing the average or the median of the distribution of these changes. This method is our second measure reported in Figure 6. This way of measuring wage inflation is less influenced by the workforce composition but does require data on wages of the same individuals over time.

To further examine this topic, we use daily data from Homebase to track workers across time and businesses, allowing us to calculate wage growth with greater frequency and flexibility. Unlike the average hourly earnings from the BLS, which averages the wages of workers and then calculates the changes, we calculate the wage changes by worker and then average the wage changes.

3.1 Methodology

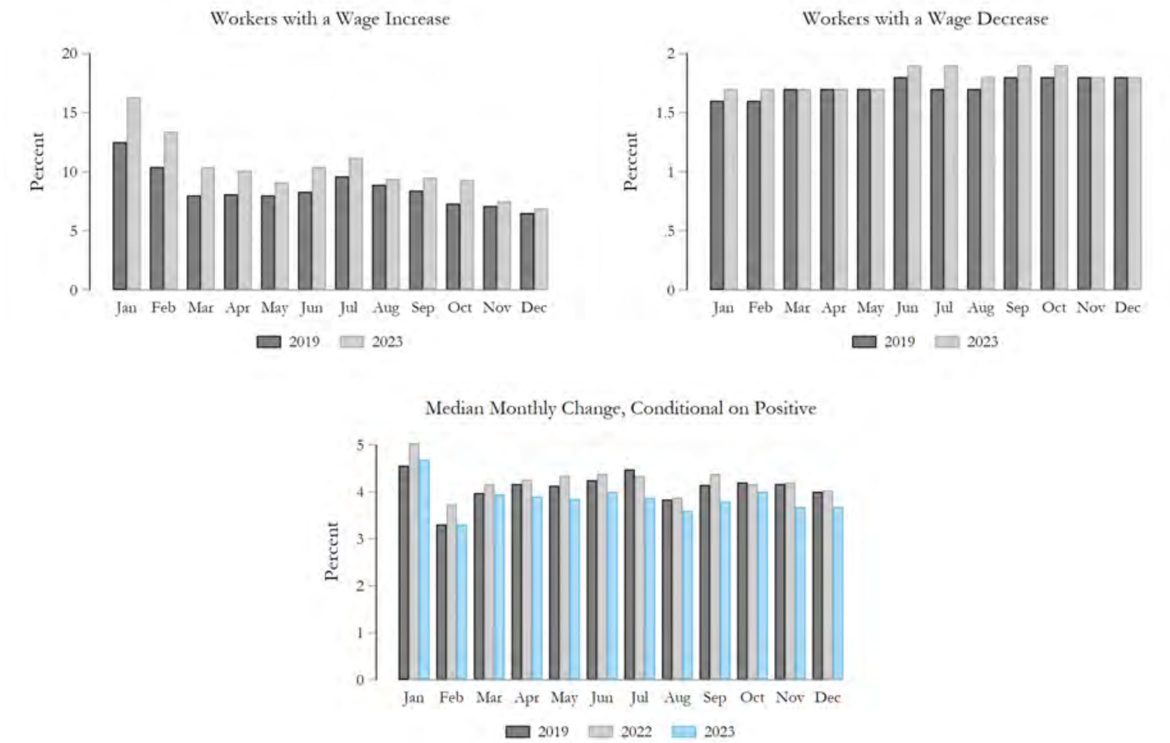
We limit our sample to U.S. workers who have been at the same company for at least one year. However, note that workers historically see larger wage increases when switching employers without an unemployment spell. Thus, since we primarily discuss job stayers in this article, our estimates of wage growth may be biased downwards.

We group individuals into individual-company pairings to account for workers with multiple jobs. We do not observe tips or other similar sources of earnings in Homebase and only have data on employers' paid wages. We also remove observations that report a wage less than \$5 per hour. Although the federal tipped minimum wage is \$2.13, several states, such as Oregon, California, and New York, have higher tipped minimum wages. Thus, workers who make less than the federal minimum wage of \$7.25 are likely food service workers who rely on tips.

We then take a daily average of each worker's hourly wage rate, weighted by hours worked, to ensure that one shift does not artificially raise wages. In Homebase, a shift wage is reported for each worker—Homebase does not differentiate between wage changes based on job title. For example, in the food industry, it is common for a manager to cover shifts for a server. In Homebase, this would show up as two shifts with two different wages, and without taking a weighted daily average, it would appear that this worker's wages decreased. Next, we take an unweighted average of an individual's wages by month.

Additionally, we only count a worker's wage as "changed" if the wage change level is at least \$0.10. This criterion ensures that only meaningful wage changes are included. Because we average a worker's hourly wage rate by month, many workers see small wage changes each month. This could be due to working overtime, working a shift under a different job title, or measurement error. By limiting our definition of wage changes

Figure 7
Months of Wage Changes



SOURCE: Homebase and authors' calculations.

to at least $0.10, we are more confident that we are looking at base wage changes. Nevertheless, our results are robust to alternative definitions of wage changes.

Next, we adjust the recorded industry information for workers in Homebase, where approximately 12 percent of workers lack an industry identifier. In cases where an industry code is reported for a worker in one shift but not every shift, we assume that the worker's industry does not change.

Our analysis begins with a description of the distribution of wage changes in the data, their seasonal patterns, and differences across sectors. Last, we discuss how the frequency and magnitude of wage changes has evolved before and after the pandemic.

3.2 Seasonality of Wage Changes

Now we examine seasonal features of wage changes, particularly how the share of workers experiencing a wage change varies by month. Figure 7 plots the share of workers with a wage increase (top-left panel) and a wage decrease (top-right panel) by month in 2019 and 2023. In both years, January and February are the months with a larger share of workers receiving a wage increase, while wage decreases are relatively uniform across all months.

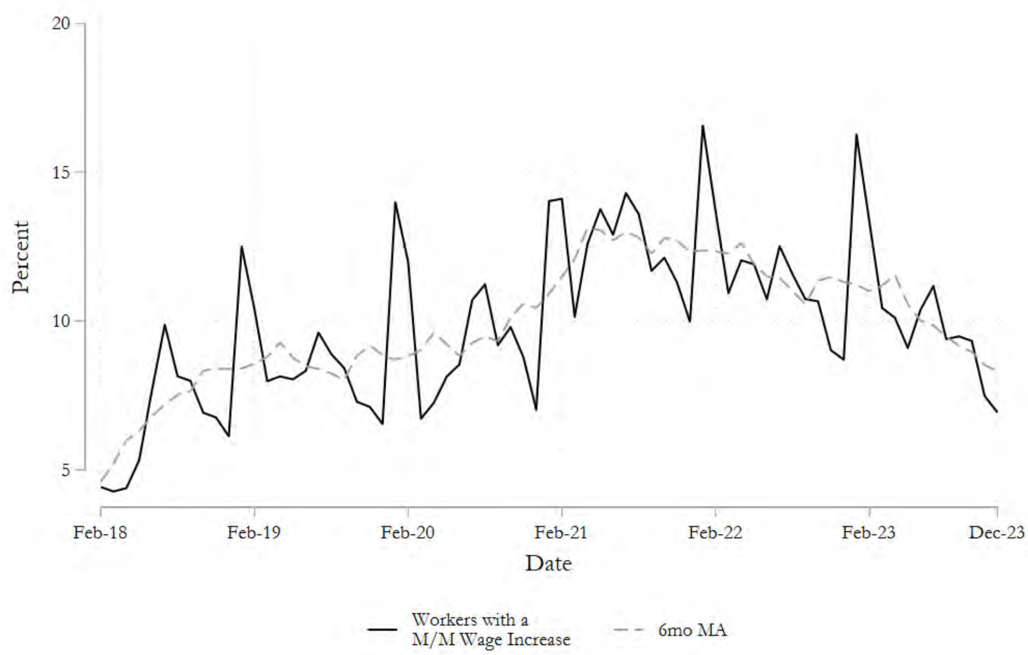
As we discuss later in more detail, we find that in 2023, more workers receive a wage increase across all months relative to 2019, but the proportion is larger in the first quarter of the year than in other periods. On the other hand, differences in the fraction of workers experiencing a wage decline are small, and the seasonality of wage decreases is generally the same in 2023 as it is in 2019.

Finally, the bottom panel shows the median wage change per month for those workers experiencing a wage increase. We find that in January the size of wage increases is larger than in other months. Additionally, in the same month, both the fraction of workers receiving an increase and the size of the increase are larger than at any other point in the year. Finally, we find that in 2022, wage increases are larger in almost all months during the year than in 2019. In 2023, the size of the wage increases is roughly similar or smaller than in 2019.

3.3 Month-over-Year Wage Changes

Next, we examine the evolution of the share of workers with wage changes. Figure 8 plots the percentage of workers with at least a $0.10 wage increase from one month to the next. To smooth the strong seasonal patterns

Figure 8
Share of Workers with a Wage Increase



SOURCE: Homebase and authors' calculations.

and gain insight into the underlying trends, we also plot a six-month-centered moving average, plotted as the dashed line. In this plot, we observe the two patterns described before. First, each year there are spikes around January and, to a lesser extent, July. Second, more workers are receiving a pay increase in 2022 and 2023 than before 2020.

As we discuss later, in 2022 and 2023 wages increased at a more rapid pace than before the pandemic. This trend was driven not only by larger wage increases for the same number of workers but also by a larger fraction of workers receiving a wage increase.

3.4 Wage Change Distribution

While means and medians provide informative summary statistics of wage changes, they may mask important underlying behavior. To reveal additional information, Figure 9 shows the distribution of yearly wage changes in 2023.[5] We find that close to 45 percent of workers experienced no wage change in a year, and very few workers experienced a wage decline. The distribution has a heavy right tail, and while the median is close to 3 percent, the mean is around 7 percent in 2023. Additionally, a significant mass of workers experienced large wage increases of 20 percent or more. Compared with the data in Grigsby, Hurst, and Yildirmaz (2021), our sample of workers has relatively fewer individuals with wage changes over a year, yet the overall shape of the distribution is similar.

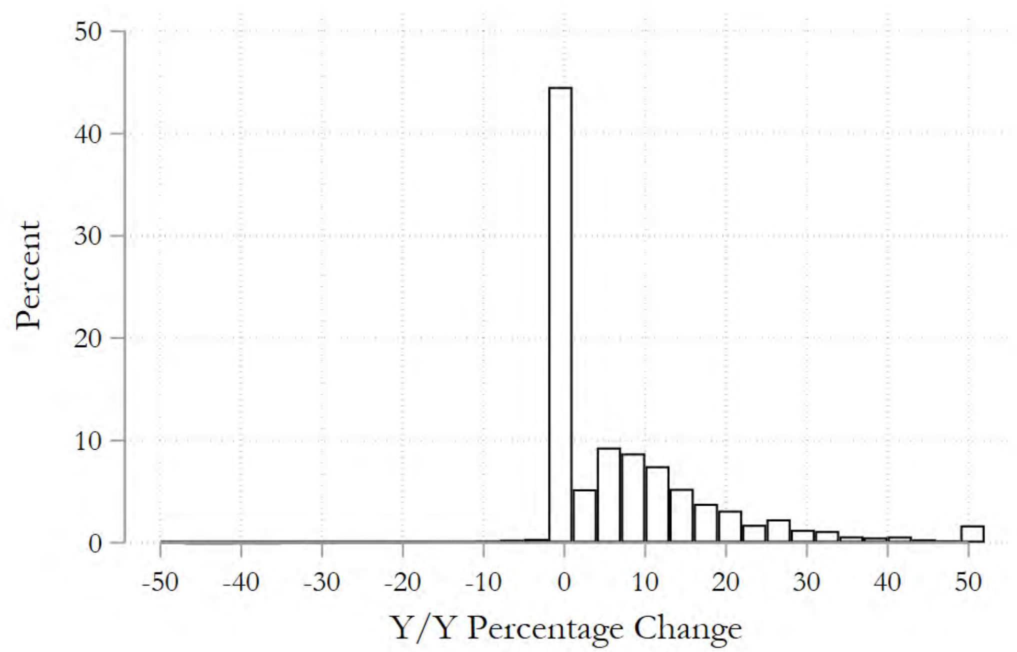
3.5 Industry-Level Wage Changes

Next, we look into the evolution of wage changes by broad sectors. We classify workers as working in a goods sector or a services sector. The goods sector includes industries such as construction, mining, agriculture, and manufacturing. The services sector includes industries such as retail and wholesale trade, transportation, healthcare, food services, and leisure. In Homebase, approximately 12 percent of workers (or employers) do not have a reported industry code. In our analysis, we do not use data on these workers, but in Appendix 1, we show in Figure A.1 that the patterns of wage changes are similar to workers in the service sector.

In Figure 10, we plot the average year-over-year wage changes of each sector from 2019 to the present. We find that pre-pandemic, both the goods and services sectors had low mean wage changes of close to 5 percent, but wage inflation increased during 2022 and 2023. For both sectors, the trends are similar: Wages began

5. We trim workers with an absolute yearly wage change greater than 200 percent and add all the mass of workers from 50 to 200 percent to the top bin shown in the figure.

Figure 9
Wage Change Distribution, 2022–23



NOTE: We trim workers with a yearly wage change greater than 200 percent and add all the mass of workers from 50 to 200 percent to the top bin.
SOURCE: Homebase and authors' calculations.

to increase more rapidly during the beginning of the pandemic, peaked in 2022, and have since decreased, although not to pre-pandemic levels. However, in the early months of the pandemic, wages for workers in the goods-producing sector increased at a faster pace but reverted to moderate levels in the second half of 2020.

On the other hand, in 2022 and 2023, wage inflation in the services sector was higher than in the goods sector, by approximately 1 percentage point. Changes in the demand for goods and services early in the pandemic relative to later years may be the reason for these patterns. During the pandemic, individuals faced important restrictions to travel, dining in restaurants, or going to in-person events. Instead, the demand switched toward the consumption of goods, putting pressure on the demand for labor in the goods-producing sector. After the pandemic, with most restrictions lifted, the demand switched to services, likely increasing the demand for services workers and their wages.

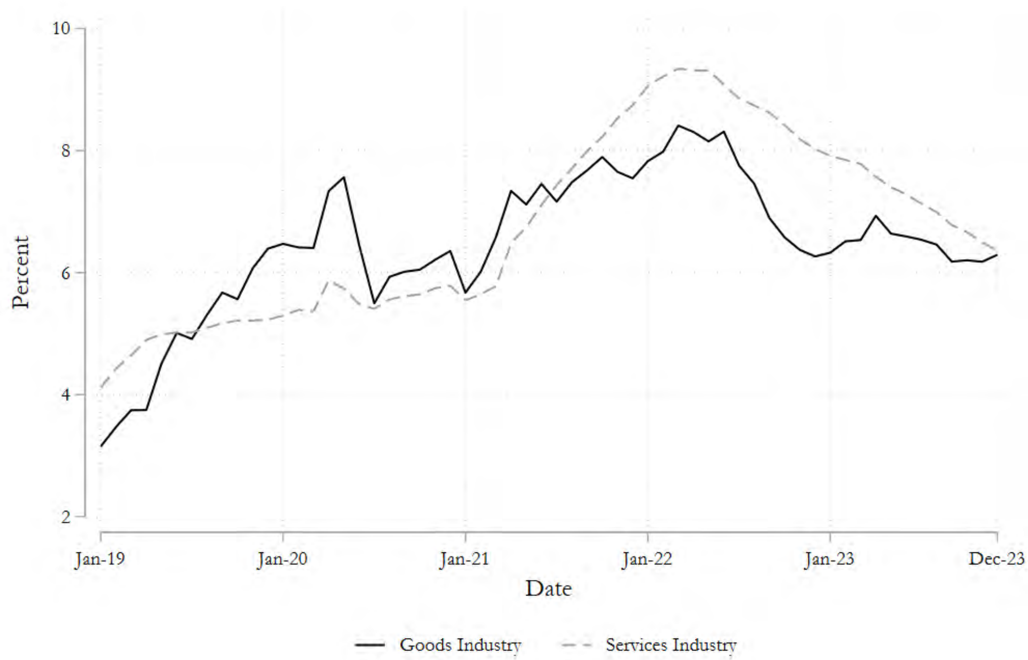
At the same time, there was substantial heterogeneity in employment between the goods and services industries during the pandemic. Many service workers could not work during the pandemic due to business shutdowns. Since we limit our sample to workers who remained at the same job for at least a year, this could bias our wage growth estimates as our calculations only use employment relationships that survived the significant employment contraction in the first half of 2020.

3.6 Recent Wage Evolution

To analyze the behavior of wage inflation before, during, and after the pandemic, we split our data into three periods: 2018–19, 2022, and 2023. This approach helps us compare labor market conditions and the evolution of wages pre-pandemic (2018–19), a high inflation period (2022), and a normalization period (2023). Additionally, we calculate wage changes over three horizons: annually, quarterly, and monthly. In the computation of some moments, such as means and standard deviations, and to avoid excessive influence of extreme values on these moments, we trim the top and bottom 1 percent of the distribution of wage changes.

We begin by analyzing the likelihood (or frequency) of a nominal wage change and how it evolved in recent years. Table 1 reports the probability of a worker getting a pay increase or decrease at different horizons. We find that the probability of a pay raise has increased since the pre-pandemic period. For example, at the annual horizon, in 2018–19, 43 percent of workers experienced a positive wage change during the year. In 2022, this probability increased to 55 percent. In 2023, 53 percent of workers experienced a pay raise—lower than in

Figure 10
Year-over-Year Wage Changes, by Industry



NOTE: We remove observations with year-over-year wage changes greater than 200 percent.
SOURCE: Homebase and authors' calculations.

2022 but still above pre-pandemic years. In 2022 and 2023, more than half of workers received a pay increase in the last 12 months. We observe similar trends at the quarterly and monthly horizons. We find that while the fraction of workers receiving a wage increase in a quarter or month is lower since most workers receive a wage increase once a year, it is higher in 2022 and 2023 than it was in 2018–19. At all three horizons, more workers received pay raises in 2023 than in 2018–19 but less than in 2022. Comparing the frequency of wage changes in the Homebase data with the estimates in Grigsby, Hurst, and Yildirmaz (2021) for the pre-pandemic years, we observe a lower frequency of wage increases in the Homebase data at the annual frequency and a slightly higher frequency of negative wage changes at the monthly and quarterly frequencies. These differences are likely driven by the different characteristics of the firms in the datasets used.

Periods of high inflation are characterized by not only larger price increases but also a higher frequency of price changes. Thus, the reduction in the frequency of wage increases in 2023 suggests a gradual normalization of wage inflation. Examining the probability of a pay cut, we do not observe substantial differences across these periods.

We now examine the magnitude of wage changes at different frequencies. In Table 2, we calculate, for each of the above horizons, the mean wage change and the median wage change, where the changes are in percent. We compute wage changes for all workers (that is, unconditional changes) and for those who received at least a \$0.10 wage increase (that is, wage changes conditional on positive changes). We also report the standard deviations. The table shows that many of the wage changes follow a similar pattern: Wages grew fastest in 2022 but are now growing more slowly in 2023. This pattern means that workers, on average, received larger pay increases in 2022 and 2023 compared to 2018–19. For example, the annual unconditional mean wage change in 2018–19 was about 4.6 percent, rising to 8.3 percent in 2022 and 7 percent in 2023. Thus, wages are still increasing rapidly but at a slower pace.

Similar patterns hold at other horizons for both mean and median wage changes. An exception is quarterly and monthly median wage changes, which are 0 percent for all three periods due to wages changing only once per year for some individuals. Large wage increases for some individuals have a larger effect on the computation of mean changes, even when trimming the top (and bottom) 1 percent of the distribution. Median changes are less affected by these large values and are lower than the mean changes. The second row of the table contains the same information as that in Figure 6. Building on these observations, wages are not only growing at a faster

Table 1
Probability of Wage Changes (Percent)

	2018-19	2022	2023
Annual			
Probability of positive wage change	42.77	55.04	52.68
Probability of negative wage change	2.48	2.09	2.26
Quarterly			
Probability of positive wage change	16.03	22.58	20.51
Probability of negative wage change	1.97	1.99	2.02
Monthly			
Probability of positive wage change	7.88	11.48	10.46
Probability of negative wage change	1.67	1.76	1.80

SOURCE: Homebase and authors' calculations.

rate on average but there is more volatility in wage changes relative to the pre-pandemic period, as evidenced by the increase in the standard deviation of wage changes. Compared with Grigsby, Hurst, and Yildirmaz (2021), we observe similar means of unconditional wage changes across all frequencies and larger means and medians conditional on a positive wage change. Our sample has a higher dispersion in wage changes, likely driven by differences in the employment composition in the two samples.

4. UNEMPLOYMENT AND WAGE GROWTH

In the previous section, we established some facts about nominal wage increases over time and showed that in the pandemic years with high inflation, wages changed more frequently and by a larger magnitude. Since this period was also characterized by tight labor markets, in this section, we analyze whether labor market conditions, as captured by the unemployment rate, are also an important determinant of wage growth. This question, the relationship between unemployment and wage inflation, has a long tradition in economics. The first economist to explore the connection between wage inflation and the unemployment rate was A.W. Phillips.[6]

Unemployment is one way to summarize the level of competition in the labor market. Phillips greatly influenced macroeconomics with his much-debated 1958 article, in which he argued that when unemployment is high, nominal wages grow more slowly, and conversely when unemployment is low, nominal wages grow more quickly. In other words, when the labor market is tight (loose), wages grow faster (slower). This relationship is often referred to as "the Phillips curve." Although the Phillips curve should be interpreted with caution, as correlation does not imply causation, this is a useful framework for viewing how labor market conditions and wage growth possibly interact.

4.1 State-Level Wage Changes

While the Phillips curve is typically studied at the national level, it can also be applied to U.S. states, where there is more heterogeneity in unemployment rates and wage inflation. For example, during the Great Recession (December 2007 to June 2009), the national unemployment rate reached 9.5 percent. At the state level, however, the highest unemployment rate during that time ranged from 4 percent (North Dakota) to 14 percent (Michigan). Given this variation among states, it makes sense that wage pressures from unemployment would also vary. This raises an important question: Does the Phillips curve still hold at the state level?

To investigate the relationship between unemployment and wage growth at the state level, we use wage data from the Quarterly Workforce Indicators from the Census Bureau and state unemployment data from the BLS. We first limit our sample to workers in the private sector from 2009 to 2023 to study the relationship before the COVID-19 pandemic. Then, we take the averages of the wages and unemployment rate for each state and year.

Figure 11 plots a data point for each state-year combination, with the year-over-year percentage change in earnings on the y-axis and the unemployment rate on the x-axis. The red line is the regression line. Its slope is –0.20, highlighting the negative relationship between unemployment and the year-over-year percentage change in wages. This finding suggests that the Phillips curve holds at the state level, albeit not perfectly.

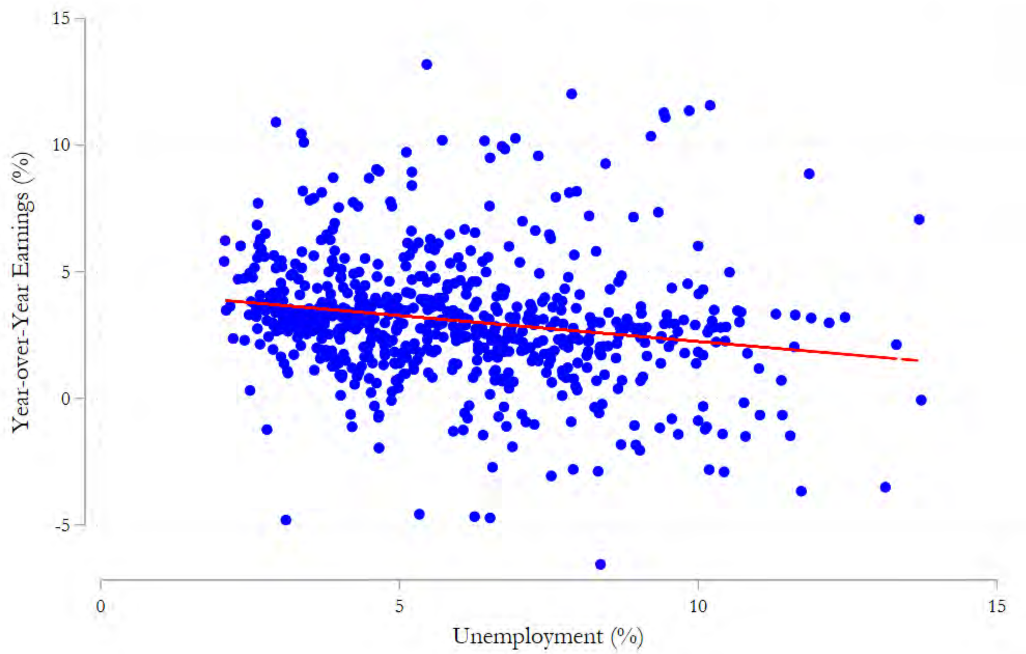
6. See Phillips, 1958, which gave rise to an extensive literature in macroeconomics.

Table 2
Wage Changes

	2018-19	2022	2023
Annual			
Mean unconditional change (%)	4.64	8.33	6.73
Median unconditional change (%)	0.00	4.35	2.78
Standard deviation of unconditional change (%)	7.62	11.29	9.60
Mean change, conditional on positive (%)	10.90	14.93	12.64
Median change, conditional on positive (%)	9.09	12.00	10.00
Standard deviation change, conditional on positive (%)	7.36	10.40	8.95
Quarterly			
Mean unconditional change (%)	1.03	1.73	1.39
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	3.11	4.33	3.71
Mean change, conditional on positive (%)	6.84	7.84	6.99
Median change, conditional on positive (%)	5.85	6.53	5.88
Standard deviation change, conditional on positive (%)	4.47	5.60	4.98
Monthly			
Mean unconditional change (%)	0.29	0.49	0.40
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	1.31	1.83	1.58
Mean change, conditional on positive (%)	4.25	4.67	4.22
Median change, conditional on positive (%)	3.62	3.85	3.44
Standard deviation change, conditional on positive (%)	2.63	3.22	2.89

SOURCE: Homebase and authors' calculations.

Figure 11
Comparing Unemployment and Wage Growth



SOURCE: Quarterly Workforce Indicators, BLS, and authors' calculations.

As the figure shows, from 2009 to 2023, the correlation between unemployment and wage growth is generally negative, while it is positive in the post-pandemic years. To further investigate the connection between unemployment and nominal wage growth, we turn our attention to individual wage growth rather than changes in average wages by states.

4.2 Individual-Level Wage Changes

Having explored the relationship between wage changes and unemployment at the state level, we now turn to our analysis at the individual level. Similar to Grigsby, Hurst, and Yildirmaz (2021), we look at the possible relationship between a worker's state unemployment rate and their month-over-month wage growth.

Using Homebase panel data, we match workers with their reported state's unemployment rate for each month.[7] This approach allows us to understand the labor market conditions at the time of employment. Next, we run regressions using four different variables linked to wage inflation, using the state unemployment rate as the main explanatory variable. The baseline regression is

$$y_{ist} = \alpha + \beta_1 U_{ist} + \beta_2 D_{2020i} + \beta_3 D_{2021i} + \beta_4 D_{2022i} + \beta_5 D_{2023i} + \beta_6 X_i + \epsilon_{ist}, \tag{1}$$

where the variable y_{ist} is one measure of wage inflation we are interested in studying, such as the probability that individual i in state s at time t experiences a wage increase or the magnitude of the wage increase for that individual. U_{ist} is the unemployment rate in state s at time t, where the individual works, and we include dummy variables for years 2020–23 to capture the average wage change in each year for the whole economy.

We also include industry fixed effects to control for persistent differences in wage changes across industries, captured in the variable X_i in the regression equation. For example, wage inflation may be greater, on average, in the construction sector than in the food services sector. Thus, including industry fixed effects in the regression allows us to estimate the relationship between unemployment and wage growth that is not influenced by persistent industry differences.

We run regressions for four different variables linked to wage inflation; these are y_{ist} in the regression. The first two regressions capture the probability that a worker experienced a wage increase or a wage change (a pay raise or a pay cut), respectively. We define a wage change to be at least \$0.10 over a month. In our sample,

7. We limit our sample to U.S. workers who have been at the same company for at least one year and have an hourly wage of at least \$5. We use data from January 2018 to December 2023.

Table 3
Regression Results

	Has Wage Increase (1)	Has Wage Change (2)	Wage Change (%) (3)	Wage Change, Conditional (%) (4)
State Unemployment Rate (β_1)	-0.073	-0.163	-0.009	-0.133
	(0.006)	(0.006)	(0.000)	(0.004)
2020 Indicator (β_2)	2.070	2.631	0.130	0.688
	(0.040)	(0.043)	(0.002)	(0.025)
2021 Indicator (β_3)	4.858	5.152	0.287	0.434
	(0.032)	(0.034)	(0.002)	(0.019)
2022 Indicator (β_4)	3.696	3.849	0.209	0.229
	(0.029)	(0.031)	(0.002)	(0.018)
2023 Indicator (β_5)	2.936	3.118	0.130	-0.200
	(0.029)	(0.031)	(0.002)	(0.019)
Observations	10,839,442	10,839,442	10,620,448	1,133,814
Mean of Dep. Var.	10.67	12.46	0.44	5.99

SOURCE: Homebase and authors' calculations.

on average, 10.7 percent of workers saw a wage increase in any given month, and 12.5 percent saw a wage change in either direction. The last two regressions capture the magnitude of the wage change for all workers and the wage change for those receiving a pay raise. In any given month, the workers in our sample saw an average wage increase of 0.44 percent; when looking only at those receiving a raise, the average increase was 6 percent.[8]

Table 3 shows the results. In all regressions, the coefficient for the state unemployment rate is negative and statistically significant. These results suggest that the Phillips curve holds also when using individual wage change data and wages increase at a faster pace and more frequently at times with tight labor markets. In particular, in times when unemployment is high in the state, relative to average, the probability that a worker experiences a wage increase (column 1) or a wage change (column 2) is lower. Moreover, in times when unemployment is high in the state, wages decline mildly (column 3). In addition, the increase in wages for workers receiving a pay raise is lower when unemployment is high (column 4).

Both the state- and individual-level data suggest that periods with low unemployment rates are also periods with more rapid wage growth. Because wages are an important component of firms' costs, a booming labor market may signal higher inflationary pressures. However, note that the year dummy variables capturing average wage changes in different years show that compared to the pre-pandemic period—which is the omitted category—nominal wage changes occurred more frequently and by a larger magnitude in the aftermath of the pandemic. Thus, while we do find that lower unemployment rates are associated with both larger month-over-month wage changes and a higher probability of a wage change, these do not fully explain the behavior of wages in recent years. This observation supports our view that wages change more frequently and by a larger amount in high-inflation years. In addition, note that inflation has moderated in 2023, and this is associated with lower levels of wage increases and a lower probability of wage changes than those observed in 2022.

5. CONCLUSION

Using individual-level data from Homebase, we study the recent evolution of wage changes for workers employed at the same firm for at least 12 months. Our results for the pre-pandemic period connect with those in Grigsby, Hurst, and Yildirmaz (2021), who study individual nominal wage rigidity in the United States. Since the U.S. economy after the pandemic has been characterized by relatively high inflation and low unemployment, we analyze whether the frequency and the magnitude of individual wage changes differs in a context of high inflation and tight labor markets. We find that individual wages increased more frequently and by a

8. In the last two regressions, we trim the top and bottom 1 percent of the distribution of wage changes so that extreme values do not overly affect the regression results.

larger amount in 2022, but with lower levels of price inflation and somewhat stable labor market conditions, the pace and frequency of individual wage increases moderated in 2023.

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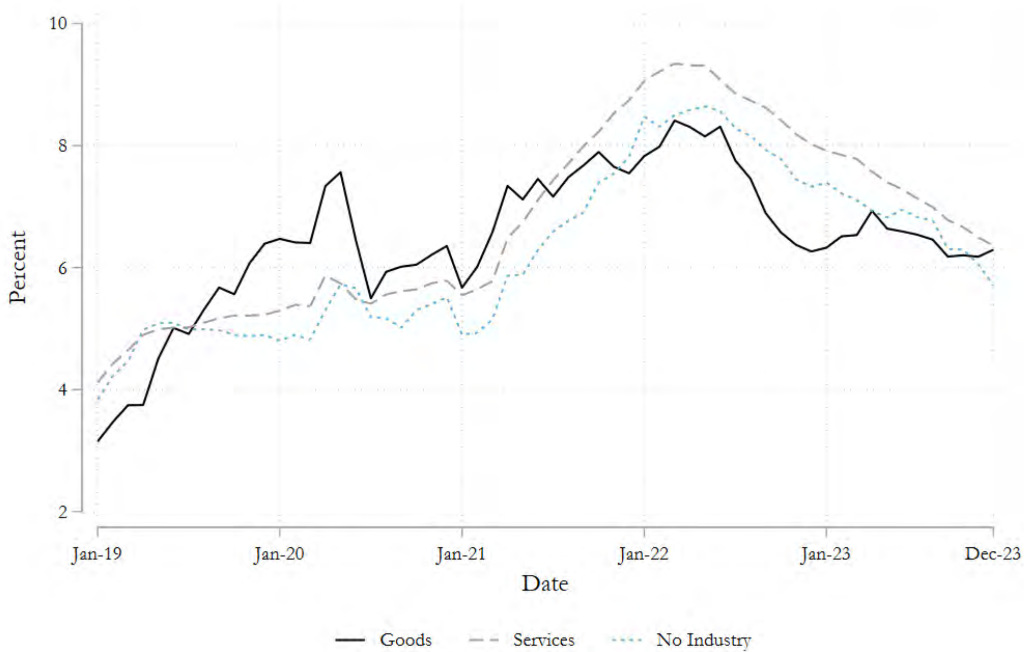
APPENDIX 1. ADDITIONAL RESULTS

In this appendix, we provide additional results to show that our main findings are robust to different industry and employment assumptions. First, we show that dropping workers who do not have an industry code does not qualitatively affect our results. Second, we repeat our analysis with different continuous employment requirements to construct our sample. We show that expanding our sample to include workers who were employed for at least six or three months does not substantively change our results.

We begin with the industry assumption we make in the main text. As mentioned in Section 3.1, approximately 12 percent of workers in Homebase do not report an industry. In Figure A.1, we plot these workers alongside the services and goods industry workers. We note that the workers who do not report an industry follow similar trends to service industry workers. Including these workers does not change our conclusions or significantly alter the observed trends in wage growth.

Figure A.1
Year-over-Year Wage Changes, Including No Industry Workers



NOTE: We trim workers with a yearly wage change greater than 200 percent.
SOURCE: Homebase and authors' calculations.

Next, we relax our sample selection requirement of each person being continuously employed for at least 12 months at the same employer. Given the large turnover of workers during the pandemic, this may be too strong of an assumption to make. Note that we do not include the results for annual wage changes. Other articles may be able to calculate a person's wage change from employer to employer. However, we can only observe workers who are employed at Homebase firms. Thus, when we relax our continuous employment requirement, we cannot calculate year-over-year wage changes for workers who are employed for less than one year. In other words, the annual probability of wage changes or the annual wage change magnitude is the same whether our sample selection criterion is 12, 6, or 3 months.

We first repeat our analysis with a sample of workers who were employed at the same establishment for at least six months. Table A.1 shows the probability of wage changes. For this group, the probability of quarterly or monthly wage increases declines, while the probability of wage decreases is approximately the same.

Table A.1
Probability of Wage Changes (Percent) for Workers Who Were Continuously Employed for at Least Six Months

	2018-19	2022	2023
Quarterly			
Probability of positive base wage change (%)	15.85	22.45	20.25
Probability of negative base wage change (%)	1.95	2.01	2.05
Monthly			
Probability of positive base wage change (%)	7.73	11.34	10.24
Probability of negative base wage change (%)	1.62	1.76	1.78

SOURCE: Homebase and authors' calculations.

Table A.2 shows the magnitude of these wage changes. The magnitude of quarterly and monthly wage changes is approximately the same for workers who are continuously employed for at least six months. An exception is the quarterly mean change of wage increases in 2023. In our original sample, we report that the average quarterly wage increase was 6.99 percent in 2023. Using a sample of workers who were continuously employed for at least six months, we report 7.06 percent. This figure further supports that wage growth was strong for many workers in 2023, even for those who were employed for less than a year.

Table A.2
Wage Changes for Workers Who Were Continuously Employed for at Least Six Months

	2018-19	2022	2023
Quarterly			
Mean unconditional change (%)	1.04	1.72	1.38
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	3.15	4.32	3.72
Mean change, conditional on positive (%)	6.93	7.84	7.06
Median change, conditional on positive (%)	5.88	6.60	5.88
Standard deviation change, conditional on positive (%)	4.52	5.57	4.99
Monthly			
Mean unconditional change (%)	0.29	0.49	0.39
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	1.30	1.81	1.56
Mean change, conditional on positive (%)	4.24	4.65	4.23
Median change, conditional on positive (%)	3.62	3.85	3.46
Standard deviation change, conditional on positive (%)	2.59	3.17	2.86

SOURCE: Homebase and authors' calculations.

Next, we relax our sample selection requirement further. We repeat our analysis with workers who were continuously employed for at least three months. Table A.3 shows the resulting probabilities of wage changes. The quarterly and monthly probability of wage increases declines for all periods, while the probability of wage decreases is approximately the same.

Table A.3
Probability of Wage Changes (Percent) for Workers Who Were Continuously Employed for at Least Three Months

	2018-19	2022	2023
Quarterly			
Probability of positive base wage change (%)	15.57	22.17	19.94
Probability of negative base wage change (%)	1.95	2.04	2.08
Monthly			
Probability of positive base wage change (%)	7.53	11.12	9.98
Probability of negative base wage change (%)	1.61	1.76	1.79

SOURCE: Homebase and authors' calculations.

Table A.4 shows the magnitude of wage changes for workers continuously employed for at least three months. The quarterly and monthly wage change magnitudes are approximately the same, except for the quarterly mean and median changes for wage raises, which show slightly stronger wage growth in 2022 and 2023. This observation further confirms that wage growth was strong for a broad range of workers post-pandemic, including those who were employed for a short period of time.

Table A.4
Wage Changes for Workers Who Were Continuously Employed for at Least Three Months

	2018-19	2022	2023
Quarterly			
Mean unconditional change (%)	1.02	1.70	1.37
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	3.14	4.30	3.72
Mean change, conditional on positive (%)	6.96	7.86	7.10
Median change, conditional on positive (%)	5.88	6.64	5.88
Standard deviation change, conditional on positive (%)	4.53	5.57	5.01
Monthly			
Mean unconditional change (%)	0.28	0.47	0.38
Median unconditional change (%)	0.00	0.00	0.00
Standard deviation of unconditional change (%)	1.29	1.79	1.55
Mean change, conditional on positive (%)	4.25	4.65	4.28
Median change, conditional on positive (%)	3.64	3.86	3.50
Standard deviation change, conditional on positive (%)	2.59	3.16	2.90

SOURCE: Homebase and authors' calculations.

Thus, we conclude that our results are robust to different sample selection criteria of employment length. We see the same wage growth trends as in the main text with different samples.