ARM Loans and Monetary Policy Transmission: Evidence from the 2022-2023 Tightening Cycle *

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Abstract

This paper examines the role of adjustable-rate mortgages (ARMs) in transmitting the Federal Reserve's 2022–2023 tightening cycle. Higher interest rates disproportionately affect households with ARM loans by increasing their mortgage payments, thereby reducing disposable income and dampening consumption. Leveraging cross-sectional variation in ARM share, we find that higher ARM share counties experience significantly lower private sector wage growth, a proxy for localized inflation. Additionally, difference-in-differences regressions show a negative relationship between ARM share and wage growth only after monetary tightening, providing a causal interpretation for our main findings. Placebo tests using government employees, whose wages are less responsive to local conditions, show no significant effects. Overall, our findings highlight more effective monetary policy transmission in higher ARM share counties, providing key insights for policymakers amid persistent inflationary pressures.

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1 Introduction

The ability of monetary policy to effectively curb inflation is a central concern for policymakers. In response to a spike in inflation, the Federal Reserve (FED) raised the Federal Funds rate in 11 out of 12 meetings from March 2022 to July 2023 leading to a cumulative increase of 525 bps (see Figure 1). Despite one of the most significant policy tightening efforts in recent history, the Consumer Price Index (CPI) rose by 9.95% and the average hourly earnings of private sector employees increased by 9.36% from December 2021 to December 2023. The limited impact of these tightening measures on inflation has prompted ongoing debate among policymakers and researchers.[1] This paper presents evidence that the U.S. mortgage market has been one factor limiting the effectiveness of monetary policy transmission during the latest tightening cycle.

One of the channels through which monetary policy affects the economy is household spending. Household spending is affected by changes in rates through their impact on debt-related expenditures such as mortgage payments (e.g., see Cloyne, Ferreira, and Surico (2020)). Mortgages are the largest household liability in most developed countries, including the US. By December 2021, the housing debt stood at $11.25 trillion dollars (FRBNY Consumer Credit Panel/Equifax). The mortgage channel posits that with higher interest rates, payments for borrowers increase and, in turn, reduce their disposable income and dampen their consumption.

The mortgage channel is more effective with adjustable-rate mortgages (ARMs) than for fixed-rate mortgages (FRMs) for at least two reasons (e.g., see Di Maggio et al. (2017)), Fuster and Willen (2017), Garriga, Kydland, and Šustek (2017), and Campbell, Clara, and Cocco (2021)). First, changes in rates affect ARM borrowers automatically through contract resets, while FRM payments only change for new loans or when existing borrowers refinance.[2]

[1] In the fall 2024 edition of the *Brookings Papers on Economic Activity* (BPEA), Romer and Romer (2024) discuss the Federal Reserve's new framework, which incorporates a more flexible average inflation target and places greater emphasis on achieving maximum employment. They identify these changes as factors contributing to the FED's delayed response to rising inflation.

[2] The refinancing option confers the right to a new loan origination, conditional on certain criteria (e.g.,

Second, ARM payments are tied to short-term interest rates, whereas FRM payments are linked to long-term rates, which are typically less responsive to policy changes.

Although ARM loans can more quickly reflect changes in monetary policy, their market share in the U.S. remains relatively low. The time-series evidence shows a steep decline in ARM share following the significant reduction in interest rates during the Great Recession of 2008–2009, with levels remaining low since then (approximately 10%).[3] Given this low aggregate market share of ARM loans, our study leverages the substantial *cross-sectional* variation in ARM market share to explore how adjustable-rate mortgages influence the transmission of monetary policy. To further justify our cross-sectional approach, we use MSA-level inflation data from December 2021 to December 2023 to highlight significant regional variations in inflation around the national CPI during this period.[4]

To implement our cross-sectional analysis, we first compute county-level ARM market share over the period 2018-2021 using the loan-level origination data from HMDA. In the absence of direct measures of inflation at the county level, we approximate *localized* inflation using county-level private sector wage growth over the period 2021-2023. We validate the use of this proxy by demonstrating a strong correlation between private sector wage growth and state-level inflation—the most granular level for which a broad panel of inflation data are available.[5]

We hypothesize that counties with a higher share of ARM loans are more affected by interest rate increases due to a higher monetary transmission rate. Specifically, given that a greater portion of loans reset at higher rates, we expect household consumption in these counties to be more constrained due to reduced discretionary spending. We refer to this hypothesis as the"local demand" channel.

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sufficient levels of income, credit score, and home equity). It is typically exercised when rates drop significantly below the original rate. However, the exercise is at the discretion of borrowers and a well-established body of research indicates that households often perceive barriers to refinancing that go beyond the actual monetary costs (e.g., Andersen et al. (2020)).

[3]See, for instance, the figures presented in `https://www.corelogic.com/intelligence/rising-rates-lead-to-increase-in-adjustable-rate-mortgage-arm-activity/`

[4]See Internet Appendix Figure IA1. The Bureau of Labor Statistics provides data for 23 MSAs.

[5]We use state-level inflation data over the 1978-2017 period provided by Hazell et al. (2022).

Our cross-sectional county-level analysis provides robust support for the hypothesis that a higher share of ARM loans is associated with a dampening effect on wage growth in the private sector from 2021 to 2023, our proxy for localized inflation. This relationship persists even after controlling for a wide range of county-level socio-economic variables, as well as accounting for state fixed effects. In terms of economic magnitude, a one standard deviation increase in ARM share corresponds to a reduction in county-level wage growth ranging from 1.1% to 2% depending on the specification, which is substantial given an average wage growth of around 10% during this two-year period.

There is a concern that counties with different ARM share levels may differ on dimensions not explicitly controlled for in our main specification. To improve comparability, we employ a matched sample approach using Coarsened Exact Matching (CEM). This technique allows for a more rigorous comparison by matching high ARM share counties with similar low ARM share counties based on observable socio-economic characteristics, though it does not address unobserved factors. Results from this matched sample analysis remain consistent with our main findings, supporting the robustness of our conclusions.

To further address the concern that counties with different ARM share levels may differ along unobserved dimensions, we employ difference-in-differences regressions to control for time-invariant heterogeneity. We use the main analysis period from 2021 to 2023 as the post-treatment period. Our pre-treatment period is from 2017 to 2019. We use this window instead of the immediate pre-period window (2019–2021) because the latter covers the height of the COVID-19 pandemic. The results show a statistically significant negative relationship between ARM share and wage growth after monetary tightening, while no such relationship exists in the pre-treatment period. This provides further support for a causal interpretation of ARM share's role in monetary transmission following the Federal Reserve's tightening of interest rates.

As a counterpoint to the private sector findings, we apply the same cross-sectional models of wage growth to government employees. The results for government employees differ sig-

nificantly from those in the private sector. In most cases, we find no effect of ARM share on wage growth in the government sector; and in the few instances of statistical significance, the effects point in the opposite direction. Overall, we observe little to no relationship between wage growth and ARM share, or only a weakly positive one, for government employees. These "placebo" results are consistent with the local demand channel, as we would not expect government wages to be affected by local consumption changes in the same way as private sector wages.

Finally, our analysis of private sector employment growth shows that counties with a higher share of ARM loans experience relatively lower growth. This finding supports the idea that stronger monetary policy transmission dampens economic activity in these areas. However, the results for employment growth are statistically and economically weaker than for wage growth, our proxy for county-level inflation. One potential explanation is the exceptionally tight labor market during our study period (2021-2023). According to Michaillat and Saez (2024), this period was the tightest since the end of World War II. Under such conditions, even if higher ARM share dampened wage growth and localized inflation, this effect might not be fully reflected in employment data given the persistent imbalance between job vacancies and job seekers.

There are several advantages to our setting. First, households likely cannot time their mortgage origination. Even if market participants could have anticipated it, the sharp rise in both inflation and the Federal Funds rate was largely unexpected, even by the Federal Reserve itself. For example, in December 2021, Federal Reserve policymakers expected rates to rise only to around 1% in 2022 and slightly below 2% in 2023.[6] Therefore, the future rate environment at reset was not foreseeable at origination, making the significant shift in rates an unexpected shock to both policymakers and households. Our focus on tightening instead of easing further mitigates endogeneity concerns as ARM resets occur independently of borrowers' credit conditions and do not depend on refinancing decisions. Lastly, our

[6]See the Fed's "dot plot" in Figure 2 of `https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20211215.pdf`

setting benefits from three key features: (1) granular county-level private sector wage growth data, affording us a proxy for localized inflation, (2) significant cross-sectional variation in wage growth during 2021-2023, improving the identification of monetary transmission effects, and (3) persistent differences in ARM share across counties prior to 2021, indicating that cross-county variation in ARM share is an ex ante characteristic. These elements enable us to identify how ARM loans influence the transmission of FED policies by examining the differential impact of monetary tightening across counties with varying levels of ARM exposure.

Our empirical design does have several limitations. The primary concern arises from the potential endogeneity of ARM share at the county level. To mitigate this issue, we include a comprehensive set of covariates in all our specifications and incorporate state-level fixed effects. Our key assumption is that, in the absence of FED tightening and after accounting for a range of observable factors and state-level fixed effects, counties with both high and low ARM shares would exhibit similar changes in private sector wage growth, our proxy for localized inflation. However, it remains possible that counties with higher ARM shares differ systematically from those with lower shares due to unobservable factors that affect both the prevalence of ARM loans and wage growth patterns. A secondary concern relates to the measurement of ARM share. We calculate it based on the county-level proportion of ARM loans relative to all mortgage originations from 2018 to 2021, which functions as the pre-period in our analysis. Financial institutions only started to report information on ARM loans in 2018 to HMDA, so we assume that this period reasonably represents the broader trends in ARM share across counties. A high degree of correlation in ARM share across origination cohorts supports the assumption that the 2018–2021 period reflects broader county-level pre-trends in ARM share.

Given the secular decline in interest rates since the 1980s and multiple recessions (e.g., 1991-93, 2001-02, 2008-09, and the recent COVID-19 downturn), most of the literature to date has focused on how fixed-rate mortgages (FRMs) dampen the effects of rate cuts (e.g.,

see Di Maggio et al. (2017), Fuster and Willen (2017))). Perhaps the most closely related paper to this study is Di Maggio et al. (2017). Focusing on the period of lower interest rates following the 2008-2009 Great Recession, they show that ARM borrowers experience (1) a substantial reduction in mortgage payments upon reset, and simultaneously, (2) a significant increase in car purchases. The impact on consumption is partially offset by voluntary deleveraging. They find heterogeneous effects, whereby low-income borrowers have a significantly higher marginal propensity to consume (MPC). Finally, and more closely related to this study, they show that regions with a larger share of ARMs were more responsive to lower interest rates, experiencing more favorable outcomes with respect to default rates, house prices, car purchases, and employment.[7]

A key contribution of this paper is to analyze the impact of the recent sharp *increase* in interest rates on the FED's primary target, inflation. To the best of our knowledge, we are the first to study how ARM loans influence the transmission of monetary policy during the 2022-2023 tightening cycle—the Federal Reserve's first major restrictive policy shift in nearly two decades. In doing so, we differ from the extant literature by highlighting how ARM loans affect monetary transmission in a rising-rate environment, offering new insights into the role of different housing debt structures on monetary policy effectiveness.[8]

There is a nascent literature studying the effects of the recent steep rise in interest rates. For instance, Liebersohn and Rothstein (Forthcoming) find that borrowers who secured a low interest FRM are more reluctant to move during the 2022-2023 period. The "lock-in" effect has been studied previously.[9] In a rising rate environment, borrowers with FRMs set at

[7]The importance of ARM loans in the transmission of monetary policies on household consumption has been documented in other countries; see Calza, Monacelli, and Stracca (2013) for a sample of (mostly European) industrialized countries, La Cava et al. (2016) for evidence from Australia, and Flodén et al. (2021) for Swedish evidence.

[8]The differential impact of ARM versus FRM loans on monetary transmission during periods of rising rates stems from two main factors. First, unlike FRM loans, which are typically less likely to be refinanced when interest rates increase—thereby only affecting new borrowers—all ARM loans are subject to automatic rate adjustments. Second, household behavior may change asymmetrically; during periods of rising rates, households are less likely to increase their leverage compared to how they may deleverage during periods of falling rates (e.g., Di Maggio et al. (2017)). This asymmetry can influence the overall effectiveness of monetary policy transmission.

[9]This latest study builds on work by Quigley (1987) and Ferreira, Gyourko, and Tracy (2010), and

lower rates (either at initiation or through refinancing) are reluctant to move as they would have to replace a low-rate mortgage with a high-rate one. This effect can refrain people from moving to take better jobs. The lock-in effect has become particularly relevant with the latest significant FED tightening. Liebersohn and Rothstein (Forthcoming) document large economic magnitudes on labor market mobility.

The remainder of the paper is organized as follows. Section 2 describes the dataset and the variables used in the analysis. In Section 3, we outline the empirical methodology and present our main findings. Section 5 concludes.

2 Data

In this section, we describe the datasets we use in our analysis: (1) mortgage origination data; (2) county-level wages and employment data; (3) other county-level data; (4) state-level wages and inflation data, as well as provide summary statistics on all county-level variables.

2.1 Mortgage Origination Data

To compute the county-level share of adjustable-rate mortgages (ARMs), we use data from the Home Mortgage Disclosure Act (HMDA), which provides the most comprehensive loan-level information on mortgages. Ideally, we would capture whether a mortgage was fixed or adjustable at the beginning of our sample for all outstanding mortgages. However, financial institutions only began reporting detailed pricing data on mortgage originations after 2017, leaving us without this information for mortgages originated before 2018. Following the HMDA data handbook published by the CFPB, we classify loans with introductory rate periods marked as "NA" or "Exempt" as fixed-rate mortgages, while all others are classified as ARMs.[10] The ARM share for each county is then computed as the number of ARM

Fonseca and Liu (2024) among others.

[10] `https://files.consumerfinance.gov/f/documents/cfpb_new-revised-data-points-in-hmda_report.pdf`.

mortgages divided by the total number of mortgages over the four-year period from 2018 to 2021.[11]

Our approach uses the ARM share computed over the four year window leading up to the significant increase in rates initiated by the FED in early 2022 as the key variable of interest. In doing so, we implicitly assume there is persistence of ARM share. Our measure based on the origination over the four-year period can be a good proxy for the ARM share for all outstanding mortgages at the onset of the monetary tightening. While we cannot directly test this assumption, we check the persistence of ARM shares within four years in Internet Appendix Table IA1. We find a very high degree of correlation (greater than 0.9) between the county-level ARM share computed over 2018-2021 (our main explanatory variable), and the county-level ARM share for each vintage in that window.

In addition, we plot the county-level ARM share in Figure 2, which reveals substantial variation across counties. The top quintile of counties has an ARM share ranging from 14% to 28%, while the bottom quintile has an ARM share between 0.5 and 5%.[12] This significant heterogeneity in ARM share is one of the key features of our data that enables us to estimate the role of ARM loans in the transmission of monetary policy.

2.2 County-level Wages and Employment Data

We obtain county-level wage and employment data from the Quarterly Census of Employment and Wages (QCEW), published by the U.S. Bureau of Labor Statistics. Our analysis focuses on the private sector, as wages and employment in the federal, state, and local government sectors are less likely to be influenced by local dynamics. We also make use of government sector wage data in our placebo tests. The QCEW provides average weekly wage data for each quarter, and monthly employment data for each month within the quarter.

[11] The reset on ARMs has built-in caps, i.e. there is a limit to the change in ARM rates that can occur at each reset. According to the Consumer Financial Protection Bureau (CFPB), the lifetime cap is typically 5% relative to the initial rate and the cap at the next reset is typically 2%.

[12] These values stem from the winsorized distribution. The unwinsorized top quintile ranges from 14% to 44%.

To account for seasonality in the quarterly wage data, we compute the average across all four quarters both in 2021 and 2023. We then calculate wage growth as the log difference between the annual averages of 2021 and 2023:

$$Wage\ growth_i = log((\sum_{q=1}^{4} AvgWklyWage_{i,2023,q})/4) - log((\sum_{q=1}^{4} AvgWklyWage_{i,2021,q})/4), \tag{1}$$

where $AvgWklyWage_{i,y,q}$ represents the average weekly wage for county i in the qth quarter of year y. We define the county-level employment growth similarly.

2.3 Other County-level Data

We include several county-level control variables in our regressions. Land area is sourced from the U.S. Census in 2010, while data on population, median household income, racial composition, the Gini index of inequality, and the unemployment rate are all obtained from the 5-year American Community Survey (ACS) in 2017. Household leverage data is sourced from the Federal Reserve in Q4 2017. Table A1 provides the definitions and sources for all these variables. All variables are predetermined relative to both the ARM share variable (computed with data post 2017), as well as wage growth and employment growth over the period 2021-2023.

2.4 State-level Data

For the state-level analysis examining the relationship between wage growth and inflation, we use QCEW data from 1978 to 2017, the period for which inflation data is available. For each quarter, we calculate the year-over-year log change in wages by comparing wages from the same quarter in the previous year to the current quarter. The year-over-year inflation data is sourced from Hazell et al. (2022).

2.5 Summary Statistics

Table 1 presents summary statistics for all county-level variables used in this study.[13] The first two rows show that the average (median) county-level wage growth from 2021 to 2023 is 10.01% (9.80%), while the average (median) county-level employment growth over the same period is 4.77% (4.46%). These figures highlight the robust economic growth observed during this period. In the third row, we report that the average share of adjustable-rate mortgages (ARMs) at the county-level stands just below 10%, with a standard deviation of approximately 6%. This indicates significant variation in ARM shares across counties.

The subsequent rows present summary statistics for several socio-economic control variables. Three of these variables—land area, population, and median household income—are log-transformed. The average median household income is around $47,000 annually, which is lower than the national median. This difference arises because the national figure is population-weighted, while our county-level median averages do not account for population size, leading smaller, lower-income counties to pull the average and median downward.

We also include a race variable, represented by the percentage of white individuals per county.[14] On average, white individuals comprise 83% of the population at the county level. Lastly, we incorporate the Gini coefficient as a measure of income inequality. The average Gini coefficient in our sample is 0.44, close to the national average. The average unemployment rate at the county level in 2017 is 6.3%, higher than the national average, a discrepancy driven by the same factors affecting median household income (i.e., smaller counties skewing the distribution). Finally, the household leverage ratio averages 1.80, indicating that total household debt levels are 1.8 times the household income on average.

[13] All variables are winsorized at the 1% level. We include only the counties with complete data for all variables, resulting in a sample reduction of less than 2.5%.

[14] The percentage of Black or African American individuals is highly negatively correlated with the percentage of white individuals (-0.86) and is excluded to avoid multicollinearity.

3 Regional Variations in Inflation, Wages, and Mortgage Markets

We begin this section by highlighting the substantial cross-sectional heterogeneity in inflation across U.S. regions, which motivates our empirical design examining the regional role of adjustable-rate mortgages (ARMs) in monetary policy transmission. Next, we provide evidence supporting the use of county-level wage growth as a reliable proxy for regional inflation. Finally, we analyze the geographical distribution and determinants of county-level ARM share.

3.1 Cross-sectional Heterogeneity in Inflation

To motivate the cross-sectional focus of our study, we first highlight the significant heterogeneity in inflation across the U.S. We illustrate this variation using regional Consumer Price Index (CPI) data from the Bureau of Labor Statistics (BLS) for all 23 Metropolitan Statistical Areas (MSAs). Figure IA1 plots MSA-level inflation from December 2021 to December 2023, revealing substantial differences relative to the national average, represented by the red horizontal line. This heterogeneity suggests potential variation in the transmission of monetary policy across regions.

Historically, the BLS has reported time-series regional inflation data only for the largest MSAs. While the inflation variation among these MSAs highlights broad cross-sectional heterogeneity, we further support these findings by complementing them with year-over-year inflation data at the state level from Hazell et al. (2022).[15] Using this data, we run regressions of annual state-level inflation on time fixed effects for the period from 1978 to 2017. The results, presented in Internet Appendix Table IA2, include two specifications. The first uses all quarterly data, resulting in overlapping observations of annual inflation, while the second uses only Q4 data, ensuring non-overlapping observations. Time fixed effects account for

[15]For detailed methodology, please refer to their paper. The data is based on non-tradeable goods and excludes both Arizona and certain quarterly observations.

variation common to all states. With an R-squared close to 0.7, the results indicate that about 30% of the total variation in inflation is not explained by time fixed effects, suggesting significant state-level variation in inflation.

3.2 Wage Growth and Inflation

Given that we have county-level data on adjustable-rate mortgages and other control variables, it would be ideal to use county-level inflation measures in our cross-sectional tests. However, such data is unavailable. Instead, we use county-level private sector wage growth as a close proxy for inflation.

To justify this choice, we demonstrate that wage growth and inflation are significantly correlated at the most granular level for which we have available data. For this, we use state-level inflation data from Hazell et al. (2022). Our first piece of evidence is graphical. In Figure 3, we plot state-level yearly wage growth over yearly inflation from 1978 to 2017. Wage growth is computed as the yearly log change in wages, and the observations—measured at the quarterly frequency—are overlapping. The binscatter plot shows a strong linear relationship between state-level inflation and wage growth.

We then test the statistical significance of this relationship using a linear regression model of wage growth on inflation. Results are reported in Table 2. In Columns (1) and (3), we regress over the full sample of overlapping quarterly data, while in Columns (2) and (4), we focus on non-overlapping data from Q4, i.e., Q4-to-Q4 annual inflation and wage growth. Columns (2) and (4) also include state-fixed effects. Across all specifications, the results show a strong statistical relationship with significance at the 1% level. Overall, these findings support the use of private sector wage growth data as a reliable proxy for county-level inflation.

3.3 Determinants of ARM Share

In this section, we investigate the determinants of county-level adjustable-rate mortgage (ARM) share over the 2018-2021 period. Since our goal is to examine the impact of ARM share on monetary policy transmission, understanding regional variations in mortgage product choices (ARM vs. FRM) is a critical first step in our analysis. As illustrated in Figure 2, significant variation in ARM share exists across the U.S., with marked differences across several state lines. These state-level differences motivate the inclusion of state-level fixed effects to control for potential unobserved, time-invariant factors at the state level which may affect county-level ARM share, such as state-specific regulations. To determine the drivers of ARM share at the county level, we estimate a series of cross-county regressions of ARM share on a number of county-level socio-economic factors. The economic specification we estimate is similar in spirit to the one used by Benmelech, Meisenzahl, and Ramcharan (2017), though applied here in the context of mortgage product choices at the county level:

$$ARMshare_i = \alpha_j + \beta X_i + \epsilon_i \tag{2}$$

where α_j is a state-level intercept (i.e. state-level fixed effects), X_i is a series of county-level socio-economic variables, namely size, population, race (percentage of white population), household wealth (median household income), income inequality (Gini coefficient), unemployment and household leverage. All these variables have been defined and described in Section 2. Standard errors are clustered at the state level.

Results for these regressions are reported in Table 3. Columns (1) through (7) report univariate regressions of ARM share on each socio-economic control separately. Smaller counties, as well as more densely populated ones, have a higher proportion of ARM share. These two results are congruent, as larger counties—in terms of land area—tend to be less densely populated. We also find that counties with greater inequality, as well as those with lower unemployment, have more ARM share. The relationship between these two

results is harder to reconcile, as greater inequality is positively correlated (0.36) with higher unemployment levels. Given the multi-layered nature of these relationships, we turn to the multivariate regression reported in Column (8), where these variables are jointly considered. In the multivariate case, all previous variables remain significant. Additionally, race—as captured by the percentage of the white population—emerges as another significant factor in explaining the variation in ARM share. A greater percentage of whites in the population is associated with a greater share of ARM loans. Overall, we find that a series of socio-economic variables significantly affect county-level variations in ARM share. Therefore, controlling for these factors will be critical to accurately assess the impact of ARM share on monetary policy transmission in our main analysis.

4 ARM Share and Monetary Transmission

By design, adjustable-rate mortgages (ARMs) expose borrowers more directly to interest rate fluctuations. As a result, debt servicing costs for households with ARM loans are more sensitive to interest rate changes, leading to more pronounced shifts in consumption. This effect is documented by Di Maggio et al. (2017), who show that households with ARM loans experience larger increases in consumption when interest rates decline.

At the regional level, we expect that interest rate increases will have a stronger impact on inflation in areas with a higher share of ARM loans. Specifically, as the Federal Reserve raises rates to curb inflationary pressures, this policy should be more effective in counties with a greater ARM share. We test this hypothesis in this section.

We break the analysis into five parts. First, we present graphical evidence at the MSA level to illustrate the relationship between inflation and ARM share. Next, we formally test this relationship at the county level, using wage growth as our key proxy for regional inflation. Third, we employ a matched sample approach using Coarsened Exact Matching (CEM) to improve comparability between counties with high and low ARM share. Fourth, we

implement a difference-in-differences analysis to address potential unobserved heterogeneity and strengthen the causal interpretation of our results. Finally, we extend our analysis by examining whether ARM share is also associated with another key macroeconomic variable: county-level employment growth. We conclude the section with a series of robustness tests to further assess the validity of our findings.

4.1 ARM Share and Inflation: MSA-level Graphical Evidence

We begin our analysis by presenting graphical evidence of the correlation between inflation and ARM share at the Metropolitan Statistical Area (MSA) level. Consumer Price Index (CPI) data for 23 MSAs is sourced from the Bureau of Labor Statistics (BLS), providing the most granular official inflation data available from the U.S. government. For each MSA, we calculate (two-year) inflation as the percentage change in CPI from December 2021 to December 2023. To approximate MSA-level ARM share and employment, we match each MSA to its most populous county and use that county's ARM share and employment figures as proxies.

Figure 4 plots MSA-level inflation against ARM share, with circle sizes proportional to regional employment. The figure reveals substantial variation in inflation across MSAs, with the highest inflation rate nearly double the lowest, suggesting differences in how monetary policy is transmitted across regions. Moreover, the best-fit line, weighted by regional employment, indicates a negative relationship between inflation and ARM share.

4.2 ARM Share and Wage Growth

Building on the findings of Section 3.2, which established wage growth as a reliable proxy for county-level inflation, we now examine the relationship between ARM share and inflation at the county level, using wage growth as our key proxy for regional inflation. Namely, we estimate the following specification:

$$\text{Wage growth}_i = \alpha_j + \beta \text{ARM share}_i + \gamma X_i + \epsilon_i \tag{3}$$

where α_j is a state-level intercept (i.e. state-level fixed effects), $ARMshare_i$ is the percentage share of ARM loans at the county level, and X_i represents the same series of county-level socio-economic variables as in Equation 2, namely size, population, race (percentage of white population), household wealth (median household income), income inequality (Gini coefficient), unemployment and household leverage. All these variables have been defined and described in Section 2. Standard errors are clustered at the state level. To account for differences in county size, all regressions are weighted by 2021 county-level employment (e.g. Mian and Sufi (2014), Benmelech, Meisenzahl, and Ramcharan (2017) and Benmelech, Guren, and Melzer (2023)).

Results are reported in Table 4. Columns (1) and (2) show estimations when only ARM share is included in the specification, while Columns (3) and (4) add all county-level controls discussed previously. Columns (2) and (4) also incorporate state-level fixed effects. Across all four specifications, we find that the relationship between ARM share and wage growth is both statistically and economically significant. The binscatter plot in Figure 5 provides additional graphical evidence corroborating the strong negative relationship between wage growth and ARM share.[16]

In terms of economic magnitude, the coefficients on ARM share in the first two specifications indicate that a one standard deviation increase in ARM share corresponds to a county-level reduction in wage growth of approximately 2% ($\approx -0.35 * 5.8$). This effect is substantial given that the average wage growth during this period was around 10%. When county-level controls are added, the economic magnitude decreases by about one third to one half, but remains economically significant.

[16]The binscatter plot is weighted by county-level employment, meaning that the average within each bin is computed using 2021 employment weights, consistent with the approach used in our regressions.

4.3 Coarsened Exact Matching Analysis

A key concern with the specification above is that counties with different ARM share levels may differ on dimensions not explicitly controlled for. To improve comparability, we employ a matched sample approach, comparing high ARM share counties with matched low ARM share counties. We first run similar regressions to those in Table 4 using a dummy for "high ARM share" counties as our key explanatory variable, instead of the continuous version of this variable.[17] The results, shown in Internet Appendix Table IA3, are consistent with the continuous specification for ARM share. However, Internet Appendix Table IA4 Panel A highlights imbalances across several socio-economic dimensions between high and low ARM share counties. To correct for these imbalances, we apply the Coarsened Exact Matching (CEM) methodology developed by Iacus, King, and Porro (2012). This approach provides a more rigorous comparison by requiring exact matches on the coarsened covariates, thus ensuring balance between treated (high ARM share) and control (low ARM share) counties based on observable characteristics. Panel B of Internet Appendix Table IA4 demonstrates that the CEM approach results in a well-balanced, though smaller, sample of 610 treatment and corresponding control counties. The matched counties exhibit no statistically significant differences across all matched dimensions.

With this matched sample of 1,220 counties, we run the following specification:

$$\text{Wage growth}_i = \alpha_j + \beta I_{\text{High ARM share},i} + \gamma X_i + \epsilon_i \tag{4}$$

The variables remain the same as before, except for the key variable of interest: $I_{\text{High ARM share},i}$ representing an indicator for counties with high ARM share. Results are reported in Table 5.

We find that the transmission channel is stronger in counties with high ARM share across all specifications. Although the statistical significance is weak (at the 10% level) when no

[17] The cutoff used was the top quintile of the ARM share distribution. The results are robust to using different cutoffs such as the top tercile or quartile.

county-level controls are added (Columns (1) and (2)), the significance improves to the 5% and 1% levels when county-level controls are included in Columns (3) and (4), respectively. Including state fixed effects significantly increases the R-squared and reduces the magnitude of the main coefficient of interest. For the specification in Column (4), which includes both state fixed effects and all county-level controls, the R-squared reaches 0.7, capturing a substantial portion of the cross-sectional variation. The coefficient of -0.75 indicates a 0.75% reduction in relative wage growth for high ARM share counties compared to matched low ARM share counterparts, a meaningful effect given the mean wage growth of 9.5% across these counties.

Overall, the results from the matched sample exercise strongly support our main regression analysis, showing that high ARM share leads to a greater transmission of the FED's tightening policy. These findings highlight the role of ARM loans in affecting regional inflation levels.

4.4 Difference-in-differences Analysis

To further address the concern that counties with different ARM share levels may differ along unobserved dimensions, we employ difference-in-differences regressions to control for time-invariant heterogeneity. We use the main analysis period from 2021 to 2023 as the post-treatment period. Our pre-treatment period is from 2017 to 2019. We use this window instead of the immediate pre-period window (2019–2021) because the latter covers the height of the COVID-19 pandemic. For the pre-period, we use the same method to compute wage growth from 2017 to 2019.

We run the following difference-in-differences regression:

$$\text{Wage growth}_{i,t} = \alpha + \beta_1 \text{ARM share}_i \times \text{Post}_t + \beta_2 \text{ARM share}_i + \beta_3 \text{Post}_t + \epsilon_{i,t}, \qquad (5)$$

where ARM share_i is the percentage share of ARM loans at the county level, consistent

with Equation 3. Post_t is an indicator variable set to 1 for 2021–2023. Standard errors are clustered at the state level. All regressions are weighted by 2021 county-level employment.

Table 6 reports the regression results. Column (1) estimates Equation 5. In Columns (2) and (3), we include county and year fixed effects, which absorb ARM share and the Post dummy. Column (3) further includes interaction terms between the Post dummy and each of the county-level variables used in Equation 3, accounting for the possibility that interest rate hikes have heterogeneous effects across counties along these dimensions. The county-level variables themselves are absorbed in the county fixed effects.

The coefficient for ARM share × Post across all three specifications ranges from -0.370 to -0.249, remaining statistically significant at the 1% level. Additionally, in Column (1), the insignificant coefficient on ARM share suggests no systematic relationship between wage growth and ARM share in the pre-treatment period. Overall, the difference-in-differences analysis strengthens our main findings by demonstrating that the observed relationship between ARM share and wage growth emerges only after the post-treatment period. This provides further support for a causal interpretation of ARM share's role in monetary transmission following the Federal Reserve's tightening of interest rates.

4.5 Placebo Tests

To provide a counterpoint to the private sector findings, we apply the same cross-sectional models of wage growth to government employees, dividing them into federal, state, and local levels. These placebo tests allow us to assess whether the observed effects of ARM share on private sector wage growth are driven by broader economic factors or are more specifically tied to local demand dynamics. The underlying hypothesis is that government employees are less exposed to local consumption changes than their private sector counterparts, and therefore, we would expect to see little to no effect of ARM share on government wage growth.

The results are presented in Table 7, with Panel A focusing on federal government em-

ployees, Panel B on state government employees, and Panel C on local government employees. Overall, we find little to no relationship between ARM share and wage growth in the government sector, providing supportive evidence for the hypothesis that government wages are less affected by local consumption fluctuations.

Panel A reports the relationship between ARM share and wage growth for federal government employees. In the first three specifications, there is no statistically significant relationship between wage growth and ARM share. Only the final specification shows a *positive* statistically significant result, with a coefficient of 0.17. A one standard deviation increase in ARM share corresponds to an increase in wage growth of approximately 1% ($\approx 0.17 * 5.8$), compared to an average wage growth of about 10% for federal government employees over the 2021-2023 period.

Panel B shows similar findings for state government employees, with mostly non-significant results. As with federal employees, only the final specification shows a *positive* and weakly statistically significant result, with a coefficient of 0.165. And again, the economic significance remains modest: a one standard deviation increase in ARM share corresponds to an increase in wage growth of approximately 1% ($\approx 0.165 * 5.8$), compared to an average wage growth of about 12.3% for state-level government employees over the 2021-2023 period. Panel C focuses on local government employees, where the results consistently show no significant relationship between wage growth and ARM share across all specifications.

A noteworthy aspect of both Panel B and Panel C is the substantial increase in R-squared when state fixed effects are included in the model. This underscores the influence of state-specific fiscal, political, and economic factors—such as state budgets, tax policies—on wage-setting for both state and local government employees. In contrast, we find that state fixed effects contribute little to explaining wage growth for federal government employees, as their pay is determined centrally at the national level and remains largely unaffected by state-level fiscal or economic conditions.

In conclusion, the results from the placebo tests further support the idea that ARM share

affects wage growth through local demand effects. While government employees, particularly at the state and local levels, show some responsiveness to state-specific factors, their wages are not sensitive to local consumption dynamics. This reinforces the notion that private sector wages are more closely tied to fluctuations in local demand and consumption, which are in turn influenced by the prevalence of adjustable-rate mortgages.

4.6 ARM Share and Employment Growth

In this final subsection, we extend our analysis to examine the relationship between county-level ARM share and private sector employment growth. Employment growth serves as an important macroeconomic indicator, and we seek to determine whether counties with a higher proportion of ARM loans experience different employment growth patterns compared to those with fewer ARM loans.

The results of our analysis are presented in Table 8. Across all four specifications, we observe a consistently negative relationship between ARM share and county-level employment growth. This suggests that higher ARM share is associated with relatively lower employment growth, further supporting the idea that ARM loans amplify the transmission of monetary policy. When interest rates rise, as they did in 2022, counties with a higher concentration of ARM loans may be more sensitive to these changes, leading to relatively slower economic activity and reduced employment growth.

However, while the direction of the relationship is consistent across specifications, the statistical significance of the results is weaker compared to our analysis of wage growth. Only in Column (3), where county-level controls are included but without state fixed effects, do we find a significant result at the 10% level. This lower significance may reflect the exceptionally tight labor market during our study period (2021-2023). According to Michaillat and Saez (2024), this period was the tightest since the end of World War II. Under such conditions, even if higher ARM share dampened wage growth and localized inflation, this effect might not be fully reflected in employment data given the persistent imbalance between job vacancies

and job seekers.

Despite the lower statistical significance, these findings provide further evidence that ARM loans play a role in the transmission of monetary policy. Specifically, ARM loans appear to influence not only regional inflation, as proxied by county-level wage growth, but also regional economic activity more generally, as reflected in county-level employment growth.

4.7 Robustness Tests

To further examine the robustness of our findings, we conduct a series of additional tests. These include augmenting our baseline regression with contemporaneous controls, incorporating a productivity measure and aggregating the analysis to the commuting zone (CZ) level.

As a first robustness check, we augment Equation 3 with additional controls that are contemporaneous to wage growth. Table IA5 presents the results. To account for changes in consumer demand driven by population shifts, we include county-level population growth from 2021 to 2023, derived from the ACS 1-year estimates. These estimates are available only for counties with a population of 65,000 or more, covering approximately one-quarter of the sample. Results in Column (1) show that the coefficient on ARM share remains unchanged.

Another potential determinant of wage growth is productivity. To construct a proxy for county-level productivity, we focus on publicly listed companies. Following İmrohoroğlu and Tüzel (2014), we first compute total factor productivity (TFP) for each public company. We then aggregate each company's TFP for 2022 and 2023, which defines our main analysis window, and map companies to counties based on their headquarters locations. For each county, we calculate the weighted average TFP of its public companies, using company employment as a weight. This approach yields a county-level productivity proxy for 476 counties. We include this measure as an additional control variable in the baseline regression. The results in Column (2) of Table IA5 show that our findings remain robust to controlling

for productivity.

While both population growth and TFP provide useful additional checks, their inclusion significantly reduces the sample size due to data availability constraints. As a result, these variables are not part of our main set of control variables but serve as robustness tests to assess the consistency of our findings.

One additional concern with our county-level analysis is that workers may reside in a different county from where they work. To address this, we re-run our analysis at the commuting zone (CZ) level. We use the 2020 Commuting Zone delineations constructed by Fowler (2024) based on workers' commuting patterns. A commuting zone comprises multiple counties, and our sample includes 582 commuting zones.

For this analysis, we first aggregate county-level data to the CZ level. We compute CZ-level wage growth by first calculating total wages at the county level—multiplying county employment by average wages—before aggregating to the CZ level. For independent variables, including ARM share, we take a weighted sum within each CZ, using county population as the weight. We assign the state of the most populous county within each CZ as the CZ's state, which is used for state fixed effects.

We employ regression specifications similar to those in Equation 3. Table IA6 presents the results. Across all four specifications, the coefficient estimates closely align with those from the county-level analysis reported in Table 4.

5 Conclusion

This study sheds light on how the structure of mortgage markets, specifically the prevalence of adjustable-rate mortgages (ARMs), influences the effectiveness of monetary policy transmission. Using county-level data, we show that areas with a higher share of ARM loans experience a stronger transmission of the Federal Reserve's recent monetary tightening, as evidenced by relatively lower wage and employment growth from 2021 to 2023. More

broadly, our findings highlight cross-sectional differences in how monetary policy impacts regional economies, emphasizing the role of mortgage structures in shaping local economic responses. This study contributes to the broader understanding of regional heterogeneity in monetary policy transmission, carrying important implications for evaluating the uneven economic effects of rising rates across different regions.

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Figure 1: Interest rates: 2014-2023

This figure shows the evolution of the Federal Funds rate (solid blue line), 30-year fixed mortgage rate (dashed red line), and 5/1-year adjustable-rate mortgage (ARM) rate (dotted green line) from 2014 to 2023.

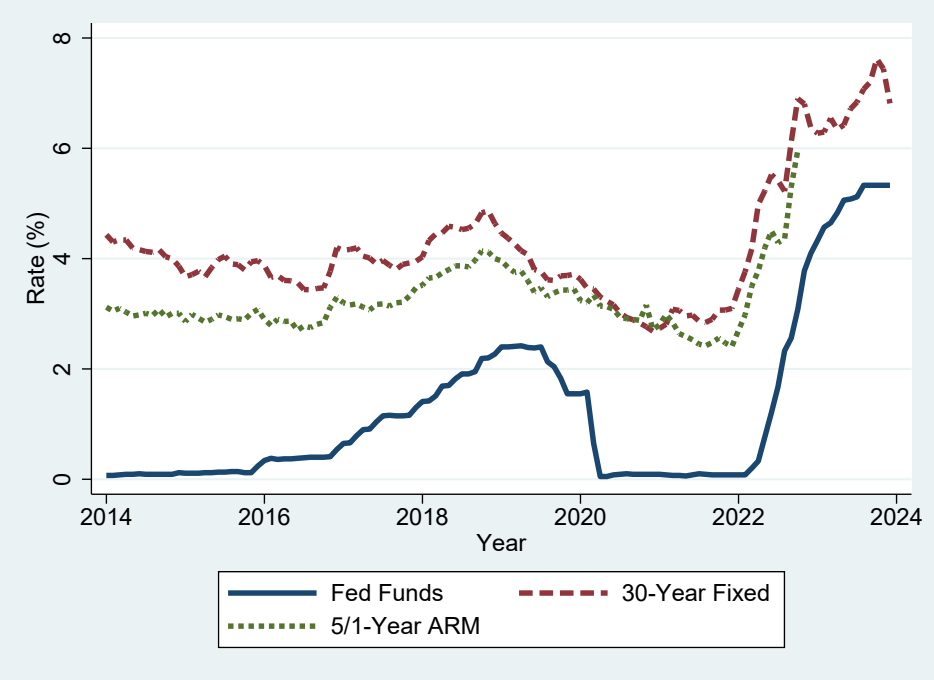


Figure 2: County-level ARM share

This figure shows county-level adjustable-rate mortgage (ARM) share based on all mortgage origination from 2018-2021. ARM share is computed by dividing the number of ARM mortgages by the total number of mortgages originated in the county.

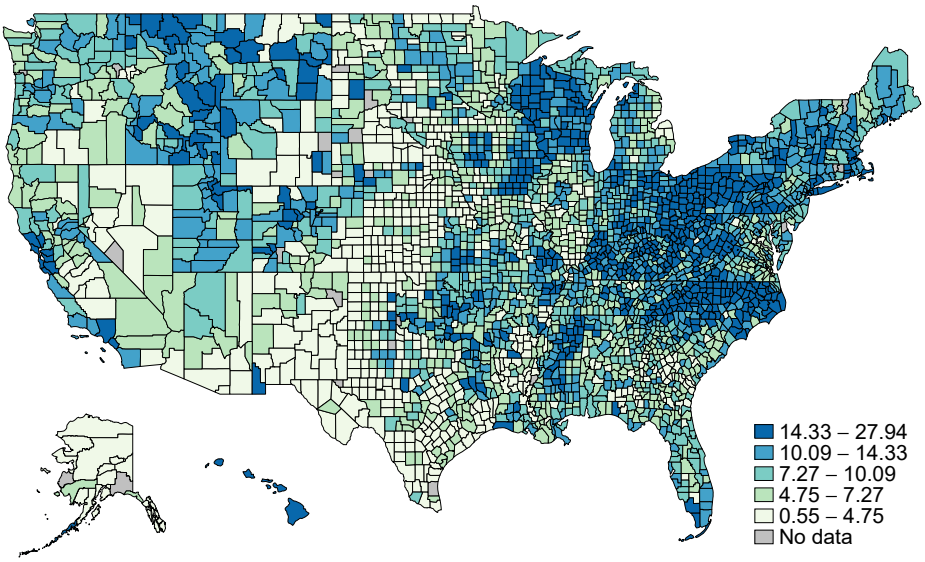


Figure 3: Wage growth vs. Inflation

This figure shows a binscatter plot of state-level yearly wage growth against yearly inflation from 1978 to 2017. Wage growth is measured as the yearly log change in wages. State-level inflation data are sourced from Hazell et al. (2022). Observations are at the quarterly frequency.

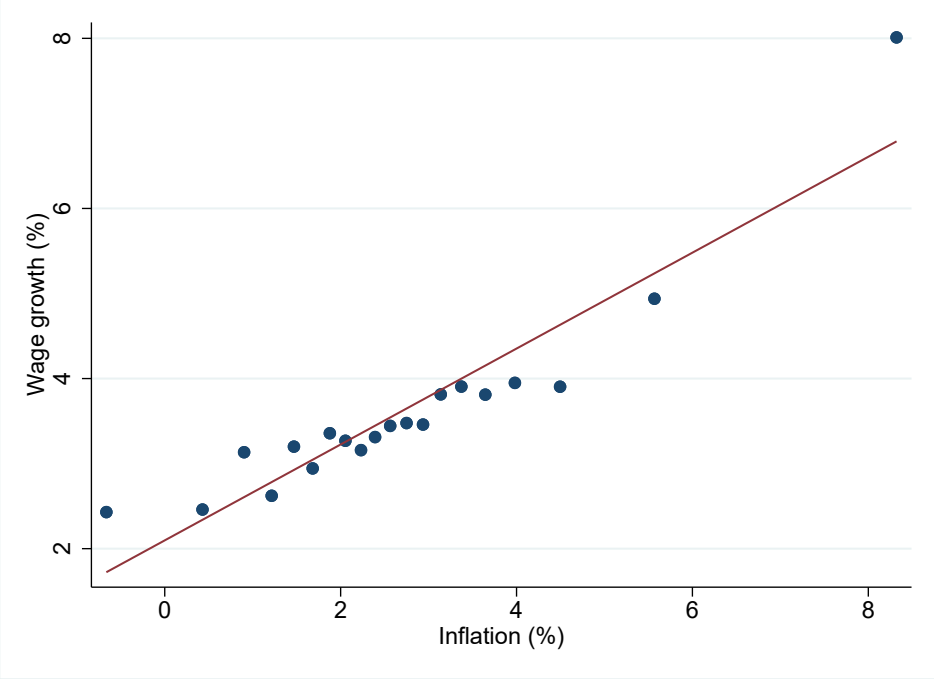


Figure 4: MSA-level CPI vs. ARM share

This figure shows a scatter plot of MSA-level consumer product index (CPI) from 2021 to 2023 against MSA-level adjustable-rate mortgage (ARM) share, calculated from 2018 to 2021. ARM share is computed by dividing the number of ARM mortgages by the total number of mortgages originated in the most populous county within the MSA. The best-fit line is weighted by 2021 employment of the most populous county within the MSA. The size of the circles is also determined by the relative sizes of each MSA based on the most populous county within each MSA.

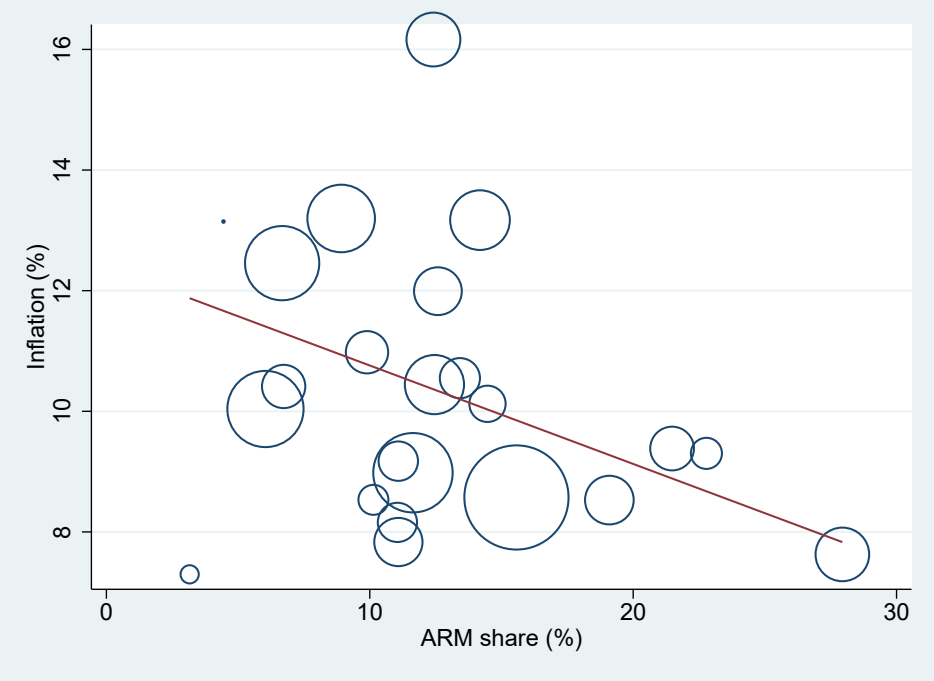


Figure 5: County-level Wage growth vs. ARM share

This figure shows a binscatter plot of county-level wage growth from 2021 to 2023 against county-level adjustable-rate mortgage (ARM) share, calculated from 2018 to 2021. Wage growth is measured as the difference between the log of average weekly wages in 2023 and 2021, using private sector wage data. ARM share is computed by dividing the number of ARM mortgages by the total number of mortgages originated in the county. The figure is weighted by 2021 county-level employment.

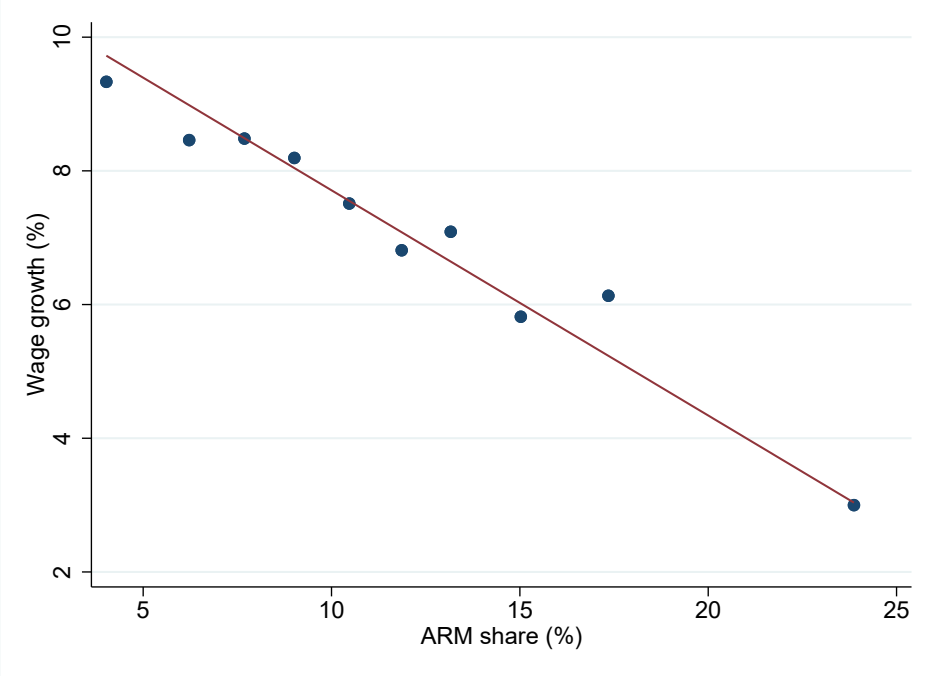


Table 1: Summary Statistics

This table reports the summary statistics of all county-level variables used in this study. Wage growth and employment growth are both computed over the two-year period from 2021 to 2023. ARM share is defined as the ratio of ARM mortgages to the total number of mortgages originated in the county between 2018 and 2021. All other variables, along with their data sources, are detailed in Appendix Table A1. The mean, median and standard deviation (SD) are reported. N represents the number of counties for which data is available.

	N	**Mean**	**Median**	**SD**
Wage growth (%)	3118	9.95	9.78	4.88
Employment growth (%)	3118	4.47	4.35	6.12
ARM share	3118	9.73	8.60	5.80
Land area, log	3118	6.49	6.42	0.82
Population, log	3118	10.29	10.16	1.44
White, percentage	3118	0.83	0.90	0.16
Median household income, log	3118	10.78	10.78	0.24
Gini coefficient	3118	0.44	0.44	0.03
Unemployment	3118	6.32	6.10	2.82
Leverage	3118	1.80	1.70	0.88

Table 2: Wage growth and inflation: State-level

This table reports the regression results of estimating the relationship between state-level wage growth and inflation. The dependent variable is state-level yearly wage growth from 1978 to 2017, measured as the log change in wages. The independent variable is yearly inflation constructed by Hazell et al. (2022). Standard errors are clustered at the state and year-quarter levels. Specifications (1) and (2) use all quarterly data, while specifications (3) and (4) use only Q4 data. Specifications (2) and (4) also include state fixed effects. t-stat are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth			
	(1)	(2)	(3)	(4)
Inflation	0.564***	0.558***	0.500***	0.489***
	(8.34)	(8.13)	(2.94)	(2.86)
State fixed effects		✓		✓
Q4 only			✓	✓
Observations	4,547	4,547	1,137	1,137
Adjusted R-squared	0.161	0.180	0.106	0.103

Table 3: Determinants of ARM share

This table reports the regression results estimating the relationship between county-level ARM share and various county-level characteristics. The dependent variable is county-level adjustable-rate mortgages (ARM) share. ARM share is computed by dividing the number of ARM mortgages by the total number of mortgages originated in the county over the period 2018-2021. All independent variables are defined in Appendix Table A1 and are measured in 2017 or earlier. Standard errors are clustered at the state level. t-stat are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ARM share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Land area, log	-0.729**							-0.731**
	(-2.27)							(-2.52)
Population, log		0.258**						0.243*
		(2.21)						(1.93)
White, percentage			1.825					2.948**
			(1.49)					(2.07)
Median household income, log				0.906				0.299
				(0.77)				(0.21)
Gini coefficient					17.552***			22.983***
					(4.86)			(4.21)
Unemployment						-0.157**		-0.149**
						(-2.43)		(-2.41)
Leverage							-0.095	-0.045
							(-0.70)	(-0.31)
State Fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,118	3,118	3,118	3,118	3,118	3,118	3,118	3,118
Adjusted R-squared	0.435	0.433	0.432	0.431	0.439	0.434	0.431	0.454

Table 4: ARM share and wage growth

This table reports the results of regressing county-level wage growth on ARM share. The dependent variable is county-level wage growth, measured as the log change in average private sector wages from 2021 to 2023. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth			
	(1)	(2)	(3)	(4)
ARM share	-0.337***	-0.358***	-0.218***	-0.194***
	(-4.14)	(-4.40)	(-3.85)	(-3.20)
Land area, log			-0.126	0.480***
			(-0.48)	(3.27)
Population, log			-0.038	-0.184
			(-0.21)	(-1.03)
White, percentage			2.568	1.762
			(1.23)	(1.04)
Median household income, log			-8.065***	-4.503***
			(-6.31)	(-3.32)
Gini coefficient			-5.885	-3.529
			(-0.92)	(-0.54)
Unemployment			-0.405***	-0.024
			(-4.58)	(-0.23)
Leverage			0.841***	0.802***
			(3.87)	(3.42)
State fixed effects		✓		✓
Observations	3,118	3,118	3,118	3,118
Adjusted R-squared	0.270	0.540	0.509	0.629

Table 5: High ARM share and wage growth: Matched sample

This table reports the results of regressions of county-level wage growth on an indicator variable for high ARM share. The dependent variable is county-level wage growth, measured as the log change in average private sector wages from 2021 to 2023. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. The High ARM share variable (ARM_high) is an indicator that takes the value of one for counties in the top quintile of the ARM share distribution. To address potential imbalances between high and low ARM share counties, we apply the Coarsened Exact Matching (CEM) methodology, which ensures exact matching on coarsened covariates. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. *t*-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth			
	(1)	(2)	(3)	(4)
ARM_high	-2.450*	-1.532*	-1.403***	-0.752**
	(-1.98)	(-1.85)	(-3.54)	(-2.12)
Land area, log			0.114	0.779***
			(0.46)	(2.95)
Population, log			0.088	0.178
			(0.25)	(0.45)
White, percentage			5.937	2.412
			(1.52)	(0.58)
Median household income, log			-10.783***	-7.877***
			(-5.20)	(-3.94)
Gini coefficient			-3.138	-8.752
			(-0.33)	(-1.27)
Unemployment			-0.352**	-0.064
			(-2.60)	(-0.39)
Leverage			1.355***	1.621***
			(3.37)	(3.55)
State fixed effects		✓		✓
Observations	1,220	1,220	1,220	1,220
Adjusted R-squared	0.087	0.452	0.589	0.698

Table 6: Difference-in-differences regressions

This table reports the results of county-level difference-in-differences (DiD) regressions. The pre-period is from 2017 to 2019 and the post-period is from 2019 to 2021. The dependent variable is county-level wage growth in the pre or post periods, measured as the log change in average private sector wages. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth		
	(1)	(2)	(3)
ARM share × Post	-0.369***	-0.370***	-0.249***
	(-3.30)	(-3.31)	(-3.70)
ARM share	0.035		
	(0.76)		
Post	5.108***		
	(5.84)		
Land area, log × Post			-0.531**
			(-2.52)
Population, log × Post			0.091
			(0.39)
White, percentage × Post			3.618
			(1.61)
Median household income, log × Post			-9.258***
			(-4.67)
Gini coefficient × Post			-9.333
			(-1.55)
Unemployment × Post			-0.281**
			(-2.19)
Leverage × Post			0.923***
			(4.07)
County fixed effects		✓	✓
Time fixed effects		✓	✓
Observations	6,234	6,224	6,224
Adjusted R-squared	0.199	0.144	0.357

Table 7: ARM share and wage growth: Placebo tests

This table presents placebo tests, with specifications identical to those in Table 4. However, instead of computing wage growth for the private sector, Panel A reports wage growth for federal government employees, Panel B for state government employees, and Panel C for local government employees. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Federal government

	Wage growth			
	(1)	(2)	(3)	(4)
ARM share	0.025	0.063	0.080	0.170**
	(0.48)	(1.01)	(1.48)	(2.36)
State fixed effects		✓		✓
Controls			✓	✓
Observations	3,128	3,128	3,128	3,128
Adjusted R-squared	0.001	0.125	0.096	0.182

Panel B: State government

	Wage growth			
	(1)	(2)	(3)	(4)
ARM share	0.038	0.061	0.104	0.165*
	(0.22)	(0.72)	(0.45)	(1.93)
State fixed effects		✓		✓
Controls			✓	✓
Observations	2,812	2,812	2,812	2,812
Adjusted R-squared	-0.000	0.599	0.052	0.608

Panel C: Local government

	Wage growth			
	(1)	(2)	(3)	(4)
ARM share	0.045	0.056	0.155	0.026
	(0.58)	(1.62)	(1.08)	(0.78)
State fixed effects		✓		✓
Controls			✓	✓
Observations	2,869	2,869	2,869	2,869
Adjusted R-squared	0.000	0.697	0.075	0.697

Table 8: ARM share and employment growth

This table reports results of regressing county-level employment growth on ARM share. The dependent variable is county-level employment growth, measured as the log change in employment from 2021 to 2023. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Employment growth			
	(1)	(2)	(3)	(4)
ARM share	-0.032	0.040	-0.113*	-0.054
	(-0.38)	(0.74)	(-1.69)	(-1.25)
Land area, log			-0.496*	-0.663**
			(-1.69)	(-2.15)
Population, log			0.745***	0.430***
			(3.79)	(2.97)
White, percentage			-1.094	-1.608
			(-0.75)	(-1.14)
Median household income, log			-1.312	1.519
			(-0.93)	(0.88)
Gini coefficient			26.256***	13.630***
			(3.79)	(3.35)
Unemployment			-0.442***	-0.164*
			(-4.02)	(-1.71)
Leverage			1.542***	1.283***
			(5.64)	(6.26)
State fixed effects		✓		✓
Observations	3,118	3,118	3,118	3,118
Adjusted R-squared	0.002	0.263	0.160	0.360

Appendix

Table A1: Variable Definition

This table provides the definitions and sources of all county-level control variables used in this paper. ACS stands for American Community Survey.

Variable	Definition	Data source
Land area, log	The logarithm of land area in 2010	Census
Population log	The logarithm of population	2017 ACS 5-year estimates
White, percentage	Percentage of white alone	2017 ACS 5-year estimates
Median household income, log	The logarithm of median income in the Past 12 Months	2017 ACS 5-year estimates
Gini coefficient	Gini index of income inequality	2017 ACS 5-year estimates
Unemployment	Unemployment rate for population 16 years and over	2017 ACS 5-year estimates
Leverage	Debt-to-income ratio in Q4 2017	Federal Reserve
Population growth	Log change in population from 2021 to 2023	ACS 1-year estimates
TFP	Weighted (by employment) average TFP for 2022 and 2023 of public companies	TFP construction follows İmrohoroğlu and Tüzel (2014)

Internet Appendix

ARM Loans and Monetary Policy Transmission: Evidence from the 2022-2023 Tightening Cycle

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Figure IA1: MSA-level Inflation

This figure shows the MSA-level Consumer Price Index (CPI) from December 2021 to December 2023. The red line represents the national-level CPI for the same period.

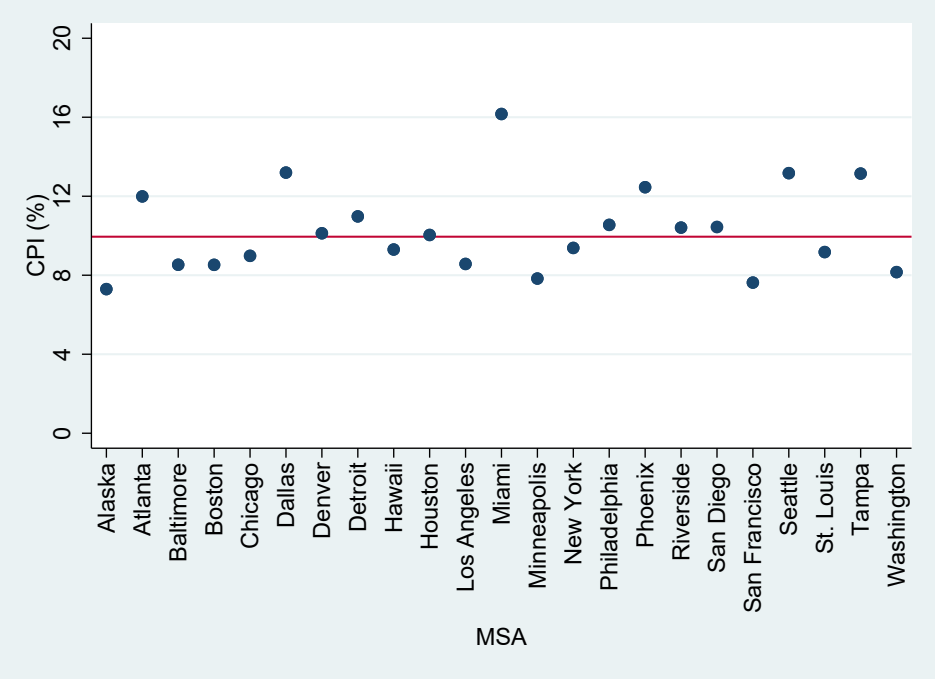


Table IA1: Persistence of ARM share

This table reports the correlation matrix of various county-level adjustable-rate mortgage (ARM) share measures, each calculated using data from a single origination year (2018 to 2021) or across all four years combined (All). Note that the ARM share measure used in the main specifications is computed across all four years combined.

	2018	2019	2020	2021
2018				
2019	0.82			
2020	0.76	0.82		
2021	0.74	0.80	0.83	
All	0.90	0.93	0.92	0.91

Table IA2: State-level Inflation and Time Fixed Effects

This table reports the R-squared and adjusted R-squared from regressing state-level inflation on time fixed effects. State-level annual inflation data are sourced from Hazell et al. (2022). Observations are at a quarterly frequency, with the sample period running from 1978 to 2017. Specification (2) includes only fourth quarter (Q4) data.

	Inflation	
	(1)	(2)
Year-Quarter fixed effects	✓	✓
Q4 only		✓
Observations	4,547	1,137
R-squared	0.689	0.696
Adjusted R-squared	0.678	0.685

Table IA3: High ARM share and wage growth: Unmatched sample

This table reports the results of regressing county-level wage growth on a high ARM share indicator variable. The dependent variable is county-level wage growth, measured as the log change in average private sector wages from 2021 to 2023. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. The High ARM share variable (ARM_high) is an indicator that takes the value of one for counties in the top quintile of the ARM share distribution. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. *t*-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth			
	(1)	(2)	(3)	(4)
ARM_high	-2.961***	-2.517***	-1.815***	-0.931***
	(-2.68)	(-2.83)	(-3.44)	(-3.20)
Land area, log			0.081	0.629***
			(0.31)	(3.57)
Population, log			-0.014	-0.098
			(-0.07)	(-0.45)
White, percentage			1.853	1.743
			(0.86)	(0.87)
Median household income, log			-9.357***	-5.644***
			(-5.73)	(-3.59)
Gini coefficient			-13.044*	-12.777**
			(-1.99)	(-2.30)
Unemployment			-0.421***	0.053
			(-4.33)	(0.51)
Leverage			0.913***	0.921***
			(4.10)	(3.11)
State fixed effects		✓		✓
Observations	3,118	3,118	3,118	3,118
Adjusted R-squared	0.131	0.432	0.474	0.608

Table IA4: Balance of Covariates

This table presents the balance of covariates between counties with low and high ARM share. In Panel A, we report the mean and number of observations (N) for the control variables, both for "Low ARM share" and "High ARM share" counties across all 3,118 counties in our sample. High ARM share is defined as counties in the top quintile of the county-level ARM share distribution. In Panel B, we apply the Coarsened Exact Matching (CEM) methodology developed by Iacus, King, and Porro (2012) to achieve balance between the treated (high ARM share) and control (low ARM share) counties. After applying CEM, the sample includes 610 treated and matched control counties. The last column tests for differences in means between the High and Low ARM share counties. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Before Matching

	Low ARM share		High ARM share		
	N	Mean	N	Mean	Diff
Land area, log	2494	6.55	624	6.26	0.29***
Population, log	2494	10.22	624	10.55	-0.32***
White, percentage	2494	0.83	624	0.85	-0.03***
Median household income	2494	10.78	624	10.78	0.01
Gini coefficient	2494	0.44	624	0.45	-0.00**
Unemployment	2494	6.33	624	6.28	0.05
Leverage	2494	1.80	624	1.78	0.02

Panel B: After Matching

	Low ARM share		High ARM share		
	N	Mean	N	Mean	Diff
Land area, log	610	6.32	610	6.28	0.04
Population, log	610	10.43	610	10.52	-0.08
White, percentage	610	0.85	610	0.86	-0.01
Median household income, log	610	10.77	610	10.77	0.00
Gini coefficient	610	0.45	610	0.45	0.00
Unemployment	610	6.54	610	6.30	0.24
Leverage	610	1.85	610	1.78	0.08

Table IA5: ARM share and wage growth: Additional controls

This table reports the results of regressing county-level wage growth on ARM share by adding additional controls to Table 4, namely (1) Population growth and (2) TFP. The dependent variable is county-level wage growth, measured as the log change in average private sector wages from 2021 to 2023. ARM share is computed by dividing the number of adjustable-rate (ARM) mortgages by the total number of mortgages originated in the county over the period 2018-2021. All control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 county-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth	
	(1)	(2)
ARM share	-0.247***	-0.248***
	(-3.42)	(-2.96)
County area, log	0.400**	0.314
	(2.23)	(1.19)
Population, log	-0.162	0.071
	(-0.55)	(0.19)
White, percentage	1.919	0.943
	(0.86)	(0.33)
Median household income, log	-4.523***	-7.354***
	(-2.96)	(-4.17)
Gini coefficient	-0.855	4.779
	(-0.12)	(0.57)
Unemployment	-0.112	-0.328
	(-0.84)	(-1.30)
Leverage	0.998***	1.374***
	(4.13)	(4.29)
Population growth	-19.976**	
	(-2.35)	
TFP		-0.136
		(-0.80)
State fixed effects	✓	✓
Observations	821	476
Adjusted R-squared	0.699	0.738

Table IA6: ARM share and wage growth: Commuting zone-level evidence

This table reports the results of regressing commuting zone-level wage growth on ARM share. The dependent variable is commuting zone-level wage growth, measured as the log change in average private sector wages from 2021 to 2023. ARM share is the weighted average (by population) of county-level ARM share within the same commuting zone. Control variables are defined in Appendix Table A1. Standard errors are clustered at the state level. t-stat are reported in parentheses. All regressions are weighted by 2021 commuting zone-level employment. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Wage growth			
	(1)	(2)	(3)	(4)
ARM share	-0.343***	-0.335**	-0.224***	-0.160**
	(-3.22)	(-2.54)	(-3.13)	(-2.32)
Controls			✓	✓
State fixed effects		✓		✓
Observations	582	582	582	582
Adjusted R-squared	0.268	0.676	0.570	0.809