Monetary Policy and Racial Inequality in Housing Markets *

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Abstract

We compile a new database of quarterly race-specific home purchases, sales, and home price appreciation for 136 U.S. cities from 1993 to 2017. We study the dynamics of local housing and labor market conditions among Black, Hispanic, and White households, and the effects of monetary policy. We find that after contractionary monetary policy, Black and Hispanic households experience a larger decrease in net home purchases and home price appreciation compared to White households. These disparities may result from less favorable labor market responses to contractionary policy among Black and Hispanic groups. Residential segregation by race further worsens the disparities in home price appreciation following monetary tightening. The findings highlight the unintended effects of monetary policy on racial housing inequality.

Keywords: Racial inequality, monetary policy, housing, homeownership, house price indices
JEL codes: E52, E40, R00

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1 Introduction

Housing inequality across racial groups remains a significant and persistent issue in the United States. Data from the US Census Bureau show that the homeownership rate for the non-Hispanic White population (hereafter "White") is 75%, whereas the homeownership rates for the non-Hispanic Black (hereafter "Black") and Hispanic populations are less than 50% each. A report by the Center for American Progress found that neighborhoods, where Black families bought homes during the 2003-2007 housing boom, saw a 7% price depreciation between 2006 and 2017, while neighborhoods with White homebuyers experienced a 2% price appreciation.[1] Housing inequality puts Black and Hispanic Americans at a disadvantage in building equity and accumulating wealth.

Although the existing literature demonstrates the sizable and significant impact of monetary policy on housing markets (see, e.g., Taylor (2007), Williams (2016)), it largely overlooks whether monetary policy influences housing market outcomes differently for different racial groups. In this paper, we address this gap, documenting for the first time how monetary policy affects home transactions and home prices for Black and Hispanic households compared to White households. Our findings demonstrate that following contractionary monetary policy, Black and Hispanic households significantly reduce net home purchases and experience greater home price depreciation relative to White households.

One of the key contributions of this paper is the creation of race-specific housing market metrics. By linking 13 million complete ownership spells from CoreLogic with racial and ethnic data from the Home Mortgage Disclosure Act (HMDA) fillings, we construct a novel database tracking quarterly race-specific home purchases, sales, and home price appreciation across 136 U.S. cities from 1993 to 2017.

Our method directly identifies the race of individual homeowners, providing a more accurate representation of race-specific housing market metrics than those based on ZIP code-level non-race-specific housing and racial composition data. For instance, an alternative approach that assumes a racial group's transaction share matches its population share within a ZIP code overestimates the purchase share for Black households (9.3% versus 5.6%) and Hispanic households (11.9% versus 9.7%). These biases are both statistically and economically significant.

Using this new database, we study the joint dynamics of local housing market outcomes and local labor market conditions, focusing on variables such as home purchases, sales, home price appreciation, employment, and earnings by racial group. Applying the method of high-frequency identification of the monetary policy surprises, we then estimate the dynamic causal effects of monetary policy on the housing market variables for White, Black, and Hispanic households and explore plausible transmission channels.

[1] See Zonta (2019), available at https://www.americanprogress.org/article/racial-disparities-home-appreciation/.

In the quantity dimension, we study the heterogeneous effects of monetary policy on net purchase intensities, measured by the log of purchase-to-sale ratio. We find that Black and Hispanic households tend to retreat from the housing market after monetary tightening. In particular, two quarters after a tightening of 25 basis points, the net purchase intensities for both Black and Hispanic households decrease by approximately 6 and 7 percentage points more, respectively, relative to White households, and by about 12.6 and 16.9 percentage points more after sixteen quarters. When examining gross purchases and sales separately, we observe that minority households have more home sales in both the short and medium run and fewer home purchases in the medium run. In sum, our findings suggest that monetary shocks significantly affect the racial composition of home buyers and sellers.

After establishing that monetary tightening disproportionately affects net home purchases for Black and Hispanic households, we turn to home price appreciation. We divide complete ownership spells by the race of homeowners and estimate repeat-sale house price indices (HPIs) at the city-quarter level for each racial group. Home price appreciation is then calculated by taking the log difference of these HPIs between consecutive quarters. The race-specific home price appreciation captures both the impact of individual homeowner race on purchase and sale prices and a neighborhood effect, due to the uneven distribution of racial groups across neighborhoods within a city. We find that the impact of monetary policy on home price appreciation varies significantly across racial groups. Sixteen quarters after a 25-basis-point increase in the federal funds rate, the cumulative decline in home prices for White households reaches 10.8%. In contrast, Black and Hispanic households experience more substantial declines, with extra drops of 5.5 and 5 percentage points, respectively. Thus, monetary tightening also disproportionately affects home price appreciation for Black and Hispanic homeowners.

What causes Black and Hispanic households to retreat from the housing market after monetary tightening? We explore two potential channels: the labor market channel and the financing channel. Our findings indicate that monetary tightening has a more pronounced impact on Black and Hispanic employment than White employment. Specifically, eight quarters after a 25-basis-point increase in the federal funds rate, White employment decreases by 0.5% cumulatively, whereas Black and Hispanic employment drops by an additional 0.9 percentage points. This disparity widens over sixteen quarters, with further declines of 1.3 percentage points for Black workers and 1.4 percentage points for Hispanic workers compared to White workers. Such reduced employment opportunities for Black and Hispanic workers after contractionary monetary policy shocks may contribute to decreased housing demand among these racial groups. Despite the varied effects of monetary tightening on employment by race, we do not find that monetary policy affects average mortgage interest rates differently for Black or Hispanic households compared to White households. Consequently, our findings suggest that the labor market channel, rather than the financing channel, is the primary factor driving changes in the racial composition of home buyers and sellers following monetary policy shocks.

The racial disparities in home price appreciation following a monetary shock may stem from either a causal relationship between homeowner race and purchase/sale prices that vary with monetary policy or from residential segregation by race. Since Black and Hispanic homeowners often reside in minority neighborhoods that depend on housing demand from their communities—demand that is more sensitive to monetary policy shocks—their home price appreciation may be more significantly affected by changes in monetary policy. To explore the role of residential segregation in these disparities, we construct and analyze race-specific home price appreciation across neighborhoods with different racial compositions. We find that within sixteen quarters of a 25-basis-point federal funds rate increase, home prices depreciate more for White (7.7 percentage points), Black (11.1 percentage points), and Hispanic (7.2 percentage points) households in minority neighborhoods than they do for households in predominantly White neighborhoods.

A limitation of our main analysis is our reliance on HMDA data to identify the race of homeowners. Since we cannot observe the race of cash buyers, our measures of home purchases and sales exclude all cash transactions. Some might question whether the observed disproportionate decline in purchases by Black and Hispanic households following monetary tightening is merely due to these racial groups shifting from mortgage purchases to cash purchases. To address this concern, we approximate the city-quarter-race-level mortgage purchase share by taking the ratio of ZIP code-based race-specific mortgage purchases to total purchases (including both mortgage and cash purchases). Although this method inherits the inaccuracies of ZIP code-based methods used to construct race-specific purchases, it represents the best possible approximation given the lack of data on the race of cash buyers. Analyzing these approximated city-quarter-race-level mortgage purchase share data, we discover that, despite monetary policy's significant effect on the substitution between mortgage and cash purchases for White households, there is no significant racial heterogeneity in this substitution pattern.

Another limitation of our approach is that we do not track households across transactions, and thus we cannot differentiate between first-time homebuyers and existing homeowners who are either moving or acquiring additional houses. First-time home purchase is particularly relevant for policy discussions.[2] To explore how monetary policy affects first-time home purchases across racial groups, we use purchases made with Federal Housing Administration (FHA) mortgages as a proxy, since most FHA loans go to first-time buyers (Lee and Tracy, 2023). Our analysis reveals that a 25-basis-point increase in the federal funds rate causes Black and Hispanic households to reduce their FHA purchases more than White households, with a difference of approximately 7.9

[2]For example, in March 2024, US President Joe Biden proposed a new tax credit that specifically benefits first-time homebuyers.

and 9 percentage points after two years, respectively. This suggests that compared to White households, Black and Hispanic households are less inclined to enter homeownership during periods of monetary tightening.

The literature highlights that racial differences in realized housing returns stem from racial differences in foreclosures and short sales (Kermani and Wong, 2021). Do the racial gaps in home price appreciation after monetary tightening also hinge on a relative increase in foreclosures among Black and Hispanic households?[3] We investigate this possibility in two steps. First, we examine how foreclosures respond to monetary policy across different racial groups. We find that while foreclosures increase for White households following monetary tightening, there are no significant differences between Black and White households or Hispanic and White households. Next, we construct a new set of race-specific home price appreciation by excluding ownership spells ending in foreclosures. Even after excluding foreclosures, we find quantitatively similar racial gaps in home price appreciation in response to monetary tightening. These findings collectively indicate that the racial gaps in home price appreciation following monetary tightening are not caused by disproportionate increases in foreclosures among Black and Hispanic households.

Thus far, our analysis has highlighted racial heterogeneity in how housing outcomes respond to monetary policy shocks. Some might hypothesize that the observed racial heterogeneity arises purely from persistent income disparities among these groups. To test this hypothesis, we investigate the racial heterogeneity in responses within specific income brackets. Using income data of mortgage applicants from HMDA, we calculate net purchase intensity and home price appreciation by race for three income groups in each city. We find that the heightened responsiveness of Black and Hispanic groups to monetary policy shocks persists even within specific income groups, indicating factors beyond income contribute to the observed racial heterogeneity. As discussed previously, one such factor is the excess responsiveness of Black and Hispanic employment to monetary policy shocks.

Do monetary tightening and expansion affect the housing market outcomes of Black and Hispanic households asymmetrically? We separate monetary policy surprises into positive and negative components and evaluate how each affects racial disparities in net home purchases, home price appreciation, and employment. The findings reveal that contractionary monetary policy disproportionately harms Black and Hispanic households compared to White households, causing greater declines in net purchases, home price appreciation, and employment. In contrast, expansionary policy does not significantly benefit these minority groups, highlighting an asymmetry in the effects of positive and negative monetary policy surprises.

Our research underscores the need for policymakers to recognize the disproportionate effects

[3] We focus on foreclosures because we cannot construct sufficiently long time series for short sales, as CoreLogic provides data on short sales for only those transactions occurring after 2006.

of monetary policy on housing outcomes for Black and Hispanic households. To mitigate these effects, policymakers might consider targeted measures such as hiring credits and employment protection subsidies to support labor market opportunities for these groups during tightening cycles.[4] Additionally, reducing residential segregation could help stabilize home values for Black and Hispanic households, alleviating racial disparities in home price appreciation during monetary tightening.

Our study contributes to the literature on the impact of monetary policy on racial inequality. Previous studies have investigated the effects of monetary policy on income inequality (Romer and Romer, 1999), consumption inequality (Coibion et al., 2017), and wealth inequality (Bartscher et al., 2022). Previous research has also explored racial disparities in employment (Bergman et al., 2022; Lahcen et al., 2023), mortgage prepayments (Gerardi et al., 2023), and inflation (Lee et al., 2021). Our paper reveals the effect of monetary policy on racial disparities in home purchases, sales, and home price appreciation and their interaction with local labor markets.

Researchers have begun to incorporate racial inequality into Heterogeneous Agents New Keynesian (HANK) models (e.g., Nakajima (2023)). However, a limitation of this attempt is its abstraction from housing dynamics. Our empirical findings suggest that the responses of home purchases, sales, and home price appreciation to monetary policy differ significantly by race, and these differences should be incorporated into future macroeconomic models of racial inequality.

Our paper expands the literature on racial segregation and housing disparities. Past work has examined historical segregation patterns (Cutler et al., 1999), zoning practices (Shertzer et al., 2016), and the effects of "redlining" (Aaronson et al., 2021). Studies have also documented racial disparities in purchase prices (Bayer et al., 2017), housing returns (Kermani and Wong, 2021), and mortgage rates (Bartlett et al., 2022). We contribute to this literature by constructing a public database of quarterly race-specific home purchases, sales, and home price appreciation for 136 cities from 1993 to 2017 and investigating racial differences in the responses of housing outcomes to monetary policy.

Our study also adds to the extensive literature on housing and macroeconomics. Notable papers that focus on the relationship between monetary policy and the housing market include, but are not limited to, Fratantoni and Schuh (2003), Iacoviello (2005), Taylor (2007), Iacoviello and Neri (2010), Bernanke (2010), Füss and Zietz (2016), Beraja et al. (2019), Eichenbaum et al. (2022), Aastveit and Anundsen (2022), and Gorea et al. (2022). In addition, recent research such as Guren (2018), Garriga and Hedlund (2020), Kaplan et al. (2020), Guren et al. (2021), and Chodorow-Reich et al. (2023) provides new insights into the dynamics of the housing market.

[4] Cahuc et al. (2019) finds that hiring credits, implemented during the Great Recession, had significant positive employment effects; Graves (2023) finds that policies that target the job destruction margin, such as employment protection subsidies (or firing taxes), are particularly effective during recessions.

While research in housing and macroeconomics has traditionally focused on residential investment, which is closely related to new home sales, a growing body of literature investigates the relationship between aggregate housing transactions, including existing home sales, and macroeconomic conditions Stein (1995); Diaz and Jerez (2013); Burnside et al. (2016); Anenberg and Bayer (2020); Ngai and Sheedy (2020); DeFusco et al. (2022); Ngai and Sheedy (2024). Aggregate housing transactions is empirically relevant because existing home sales are much larger and often more volatile than new home sales.[5] Our paper contributes to this literature by examining how monetary policy affects housing transactions across racial groups and how these impacts vary by neighborhood characteristics within cities.

The remainder of the paper is organized as follows. Section 2 provides an overview of the microdata used in our analysis and describes how we aggregate these data to create race-specific housing market measurements at the city-quarter level. Section 3 presents our main empirical findings, focusing on the effects of monetary policy shocks on race-specific home purchases, sales, and home price appreciation, along with an investigation of potential transmission mechanisms. Section 4 explores the effects of residential segregation, the substitution of cash and mortgage purchases, home purchases made with FHA loans, foreclosures, and foreclosure-free HPIs, and the impacts of income, while also examining the asymmetric effects of monetary policy. Section 5 offers concluding remarks. Additional details are available in the appendices.

2 Data and Race-specific Measurements Construction

We focus on three racial groups in our analysis: non-Hispanic White, non-Hispanic Black, and Hispanic (of any race), hereafter referred to as White, Black, and Hispanic, respectively. Our analysis does not include American Indians, Alaska Natives, Asians, Native Hawaiians, or other Pacific Islanders due to data limitations.[6] In section 2.1, we provide an overview of the underlying microdata, and in section 2.2, we present our methodology for calculating home purchases and sales and constructing HPIs for the three racial groups across 136 US cities. We also compare our approach with alternative methods to highlight its advantages. We briefly describe other data used in this study in section 2.3. Our study also heavily relies on measures of monetary policy surprises, which we discuss in greater detail in section 3.1.

[5] For instance, between January and April 2020, existing single-family home sales dropped from approximately 4.8 million to 3.5 million, while new single-family home sales decreased from 0.7 million to 0.55 million.

[6] Specifically, we do not have a sufficient number of complete ownership spells in our sample to construct HPIs for these racial groups at the city level.

2.1 CoreLogic–HMDA data

Our analysis uses housing market data sourced from CoreLogic, which provides linked information on housing and mortgage transactions collected from public tax and deed records. For each housing transaction, we have access to the date, price, and location. For each mortgage transaction, we observe key information such as the date, loan type (conventional, FHA, or VA), loan amount, lender name, and (whenever available) mortgage interest rate.[7]

Since CoreLogic does not provide race and income information about homebuyers, we match the CoreLogic data with the HMDA filing data. HMDA filings capture the near-universe of mortgage originations. The publicly accessible version of HMDA includes information on application year, loan type, loan amount, lender decision, and applicant demographics such as income, race, ethnicity, gender, and location (state, county, and census tract). If a co-applicant is present, their race and ethnicity are also documented. The data also provide useful information on the lender, such as the name of the institution. HMDA data became available in the early 1990s.

In linking CoreLogic and HMDA data, we follow an approach similar to that employed in previous studies (e.g., Bayer et al. (2016)). For each mortgage transaction in the CoreLogic data, we search for matching mortgage applications in the HMDA data based on the exact year, census tract, loan type, and loan amount. We refine the list of possible matches based on the textual similarity of lender names, retaining only high-quality matches. Our overall matching rate is 54%, which is in line with the matching rate in Bayer et al. (2016).

We derive our racial and ethnic variables from the HMDA data and apply the following coding methodology. When the applicant and any co-applicant identify as White and non-Hispanic, the household is categorized as White. Similarly, if the applicant and any co-applicant identify as Black and non-Hispanic, the household is categorized as Black. If both the applicant and any co-applicant identify as Hispanic, the household is categorized as Hispanic. Since 2004, applicants and co-applicants have had the option to report multiple races in their HMDA filings. When classifying households as White or Black, we include only those that report a single race. However, we allow households in the Hispanic category to identify multiple races.[8] Appendix A provides further details about the HMDA data, the matching procedure, and our coding method for racial and ethnic variables.

One possible question about our approach is whether our linking procedure invites selection bias. To address this question, we analyze the matching rate along three observable dimensions: house price, neighborhood White population share, and neighborhood median income. The results

[7]Conventional mortgages are not backed by a federal agency. FHA loans are backed by the Federal Housing Administration. VA loans are backed by the US Department of Veterans Affairs.

[8]The following categories of households are excluded from our analysis: interracial households, households that identify with multiple races, non-Hispanic Asians, non-Hispanic Pacific Islanders, and instances in which only the applicant or co-applicant is Hispanic.

are presented in Appendix Table A.1. The analysis reveals that our matching rate remains the same across house price, neighborhood White population share, and neighborhood median household income, indicating that there is no evidence of selection bias in these observable dimensions.

We reformat the CoreLogic–HMDA data into a sample of ownership spells and keep only the completed spells in which both purchases and sales are observed. We include in our analysis arm's-length single-family home transactions, except those in which a house is purchased without a mortgage or by a corporation. We exclude cases in which a house is sold within six months of purchase. Our final sample of microdata from the CoreLogic–HMDA dataset comprises more than 13 million completed ownership spells. All purchases in the sample were made between 1993 and 2017 and all sales were completed by the end of 2021.[9,10] Summary statistics of the microdata are available in Appendix Table A.2.

2.2 Race-specific Measurements Construction

Race-specific home purchases and sales We follow the convention of the Federal Housing Finance Agency (FHFA) and aggregate data at the metropolitan level. This includes both Metropolitan Statistical Areas (MSAs) and, when available, Metropolitan Divisions (i.e., subdivisions of MSAs). We refer to each as a 'city.'

We use the matched CoreLogic–HMDA data to calculate home purchases and sales by race at the city-quarter level. We compute both raw counts and dollar volumes. In our empirical analysis, we focus on the net home purchase intensity measured by log(raw count of purchases/raw count of sales), but our results are qualitatively similar if we use dollar volumes instead.

Our measures of home purchases and sales have two limitations. First, our measure of home purchases includes entries into homeownership, upgrades, and purchases of second homes. Likewise, our measure of home sales includes exits from homeownership, downgrades, and sales of second homes. Measuring entry and exit of homeownership requires us to track individual market participants across properties and time, which we cannot do with high confidence given the limited individual-level information available in the CoreLogic–HMDA data. Second, since we

[9]We start the sample in 1993 because HMDA data before 1992 uses the 1980 census tracts, whereas data from 1993–2002, 2003–2011, and 2012–2017 use the 1990, 2000, and 2010 census tracts, respectively. To align these tracts, we use census block relationship files from the US Census Bureau's website (https://www.census.gov/geographies/reference-files/2010/geo/relationship-files.html). Including data before 1992 would lead to significant data loss.

[10]Purchases made after 2017 have been excluded from the sample due to changes in the reporting methods of the HMDA. Specifically, before 2018, loan amounts were rounded to the nearest thousand dollars in HMDA data. However, as a result of the 2015 HMDA Rule, loan amounts are publicly disclosed in the post-2018 HMDA data at the midpoint of the $10,000 interval that encompasses the reported value. For instance, a loan amount of $198,600 would have been rounded to $199,000 in HMDA data before 2018, but in HMDA data from 2018 onwards, it would be rounded to $195,000. The suppression of details in the publicly accessible version of HMDA after 2017 makes linking CoreLogic and HMDA data less reliable.

rely on HMDA data to identify the race of homeowners, we necessarily exclude all cash transactions, which lack corresponding HMDA data, from our measures of home purchases and sales. To address these limitations, we also measure home purchases made with FHA loans, the share of mortgage purchases across all home purchases, foreclosures, etc. Details of these additional measurements are discussed in section 4.

To evaluate whether monetary policy influences racial inequality in the housing market through heterogeneous pass-through to purchase mortgage interest rates by race, we calculate the average interest rates of 30-year conventional purchase mortgages at the city-quarter-race level. Furthermore, we compute at the city-quarter-race level the share of FHA mortgages and the average loan-to-value (LTV) ratio, which we include as additional control variables in the robustness checks.

Table 1 provides summary statistics of key variables. Among Whites, the average number of home purchases per city-quarter is 697, significantly higher than the numbers found among Blacks and Hispanics, which are 64 and 119, respectively. The White group has an average of 622 sales, again a higher count than either of the other groups. The average mortgage rate across cities and quarters is 5.1% for White borrowers, which is notably lower than the 6.6% for Black borrowers and the 6.2% for Hispanic borrowers.

After constructing race-specific home purchases and sales, we produce these variables at a more detailed level, utilizing either race and neighborhood White population share or race and income as criteria. In the former case, we classify households into three distinct categories based on the White population share within their census block group, thereby distinguishing among neighborhoods with low, moderate, and high concentrations of White residents. In the latter case, we categorize mortgage applicants into three equally sized income groups (low, middle, and high) for each city-quarter. In both instances, we calculate home purchases and sales for a total of nine groups. Further details regarding the summary statistics of home purchases and sales at these more granular levels are available upon request.

Race-specific HPI and home price appreciation We construct quarterly city-level repeat-sale HPI series using the linked CoreLogic – HMDA data for different racial groups. To do so, we extend the canonical log-linear model of house price change by allowing the average appreciation in home prices to vary by homeowner race. Specifically, we split our sample of complete ownership spells by city and race of homeowners and estimate the following regression model separately for each city l and race r:

$$\log p_{i,l,t'} - \log p_{i,l,t} = b^r_{l,t'} - b^r_{l,t} + \varepsilon_{i,l,t,t'}.$$

In the equation above, t' and t are the sale and purchase quarter, respectively; $p_{i,l,t'}$ and $p_{i,l,t}$ are the sale and purchase price of house i, respectively; r is the race of the individual owning house i from t to t'; and $\varepsilon_{i,l,t,t'}$ is an idiosyncratic shock with mean zero. $b^r_{l,\cdot}$ are coefficients to be estimated, with

Table 1: Summary Statistics of Key Variables at the City-Quarter-Race Level

(a) White	count	mean	sd	p10	p50	p90
Purchase	8,488	696.7	842.8	112.0	413.0	1613.0
Sale	8,488	622.0	730.9	89.0	368.0	1498.0
Purchase Dollar Volume	8,488	190723.2	262787.0	24144.5	100161.2	456943.0
Sale Dollar Volume	8,488	188574.1	294984.8	16133.6	83439.0	501456.0
Average Mortgage Rate (%)	7,907	5.1	1.6	3.3	5.0	7.4
(b) Black	**count**	**mean**	**sd**	**p10**	**p50**	**p90**
Purchase	8,488	63.4	185.5	3.0	19.0	145.0
Sale	8,488	60.3	142.3	3.0	20.0	149.0
Purchase Dollar Volume	8,488	12722.3	38265.1	506.0	3650.1	26202.5
Sale Dollar Volume	8,488	11070.0	26211.1	352.5	3013.9	26428.8
Average Mortgage Rate (%)	4,296	6.6	2.0	3.6	6.9	9.0
(c) Hispanic	**count**	**mean**	**sd**	**p10**	**p50**	**p90**
Purchase	8,488	119.4	324.9	4.0	27.0	286.0
Sale	8,488	108.8	269.2	3.0	24.0	283.0
Purchase Dollar Volume	8,488	29949.1	115148.7	687.3	4818.7	57998.7
Sale Dollar Volume	8,488	25237.2	73289.5	381.0	3535.7	61486.7
Average Mortgage Rate (%)	4,813	6.2	1.9	3.4	6.5	8.6

Notes: Purchase and Sale represent the raw counts of home purchases and sales at the city-quarter-race level. Purchase Dollar Volume and Sale Dollar Volume refer to the aggregated prices of home purchases and sales at the city-quarter-race level, measured in thousands of dollars. Average Mortgage Rate represents the average interest rate of 30-year conventional purchase mortgages for each city-quarter-race combination.

$b^r_{l,t}$ representing the log HPI of race r in city l and quarter t.[11] Note that $b^r_{l,t'} - b^r_{l,t}$ is the average appreciation in home price for race r from t to t'. If the average appreciation in home price is common across racial groups, the estimated log HPI series ($b^r_{l,t}$) should be the same across r. Conversely, if the estimated log HPI series varies by racial group, we know that different racial groups experience unequal home price appreciation. For each race that we study, we estimate the coefficients $b^r_{l,\cdot}$ using linear regression on cities with at least 200 complete ownership spells. Following Guren (2018), we adopt an interval-weighting procedure that uses as weights the reciprocal of the standard deviation of the prediction error by quantiles of the length of the ownership spell. We then construct (nominal) HPI series and home price appreciation from estimated $b^r_{l,\cdot}$ for each racial group.[12] Our baseline estimates of race-specific HPI series include ownership spells that end in foreclosures. But since foreclosures can strongly affect the estimated race-specific HPI series, we also produce a set of race-specific HPI series that exclude foreclosures. Details of foreclosure-free

[11] $b^r_{l,t}$ is normalized to zero in the base year for all races.

[12] In this paper, home price appreciation refer to average appreciation in home price, calculated as log differences of HPIs at different points in time.

HPIs are discussed in section 4.4.

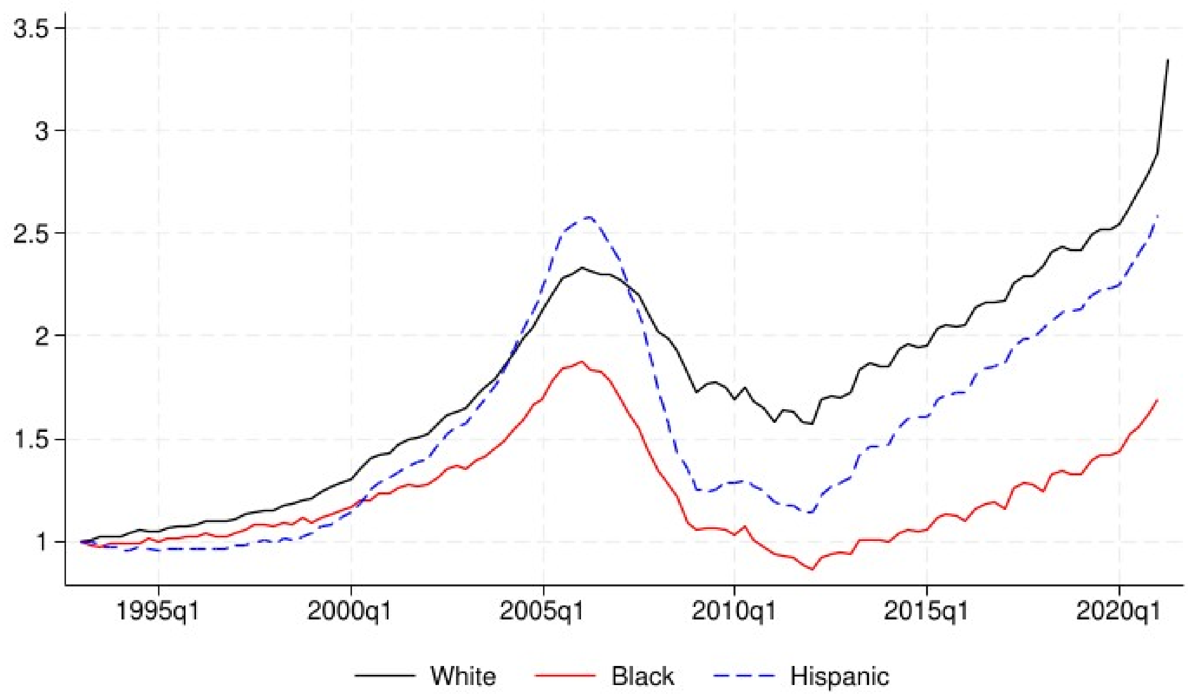
Our database is not fully balanced due to constraints in data availability. In regression analysis, we include only cities and quarters in which all three racial groups have recorded data for home purchases, sales, and HPIs. Furthermore, we require that each city in our regression sample appear in at least 20 quarters to capture broad temporal variation. Similarly, we require that each quarter in our regression sample includes data from at least 20 cities to capture the broad spatial variation for each period. These restrictions enhance the generalizability of our findings by creating a more balanced dataset, reducing the influence of anomalies in specific cities or quarters, and thus making our estimates more robust. Our final regression sample spans from 1995Q3 to 2017Q4 and includes 136 unique cities.[13] The list of cities and a map of their geographic distribution are provided in Appendix B.

Finally, we estimate national-level HPIs by homeowner race, as shown in Figure 1. Our national HPIs by race are biased toward price trends in urban areas because CoreLogic sources its housing transaction data from county recorders, which do not cover all US counties, particularly rural ones.[14] Table 2 provides summary statistics of quarterly home price appreciation implied by national HPIs for White, Black, and Hispanic homeowners. The first two columns document the mean and variance of quarterly home price appreciation across racial groups. White households experienced a higher and less variable home price appreciation. The last three columns document the correlations of quarterly home price appreciation and output gaps with 4-, 8-, and 20-quarter leads. We find that exceptionally high home price appreciation usually predate a positive output gap, and the relationship is similar across racial groups.

[13]For context, the FHFA Purchase-Only Indexes, which are non-race specific and estimated using sales price data, are available for the 100 largest MSAs on their website https://www.fhfa.gov/data/hpi/datasets?tab=quarterly-data. Our final dataset covers 86 of these MSAs, with the reduction from 100 to 86 almost entirely due to our requirement that there be a sufficient number of transactions to construct race-specific HPIs for all three racial groups.

[14]For a non-race-specific HPI, this bias can be corrected by combining county recorder data with home value data from the public version of the Freddie Mac Single-Family Loan-Level Dataset using appropriate weights. However, this correction cannot be implemented for race-specific HPIs because it is not possible to reformat the Freddie Mac data into a sample of ownership spells and identify the race of individual homeowners.

Figure 1: National HPIs for White, Black, and Hispanic Homeowners



Notes: This figure plots the time series of point estimates of the national HPIs for White, Black, and Hispanic homeowners. All indices are normalized to 1 in 1993Q1.

Table 2: Summary Statistics of quarterly home price appreciation for White, Black, and Hispanic Homeowners

	mean	variance	corr with Δy_{t+4}	corr with Δy_{t+8}	corr with Δy_{t+20}
White	1.07	6.66	0.26	0.33	0.06
Black	0.47	9.74	0.24	0.34	0.08
Hispanic	0.85	11.40	0.30	0.41	0.09

Notes: This table presents the mean and variance of quarterly home price appreciation implied by national HPIs for White, Black, and Hispanic homeowners and the correlation between quarterly home price appreciation and the output gaps with 4-, 8-, and 20-quarters leads. The quarterly home price appreciation is calculated as log differences of HPIs between two consecutive quarters and given as percentages. The output gap is computed as 100*(GDP-potential GDP)/potential GDP, where the GDP and potential GDP are obtained from Federal Reserve Economic Data (tickers: GDPC1 and GDPPOT).

Comparing race-specific housing metrics: CoreLogic–HMDA versus ZIP code-based methods Our method of constructing race-specific housing market metrics relies on linking CoreLogic data with HMDA data to accurately determine the race of individual homeowners. Below, we briefly outline the advantages of our approach over alternative non-race specific ZIP code-based methods. Additional details and results are provided in Appendix C.

An alternative method to construct race-specific purchases (or sales) in a city requires only the racial composition of each ZIP code and the number of purchases (or sales) in each ZIP code. Specifically, let z represent a ZIP code. For a given city l, quarter t, and racial group r, the alternative measure of $\text{Purchase}_{l,t,r}$ is calculated as $\sum_{z\in l} \text{Purchase}_{z,t} \times \frac{\text{Population}_{z,t,r}}{\sum_r \text{Population}_{z,t,r}}$, where the summation over z covers all ZIP codes within city l.

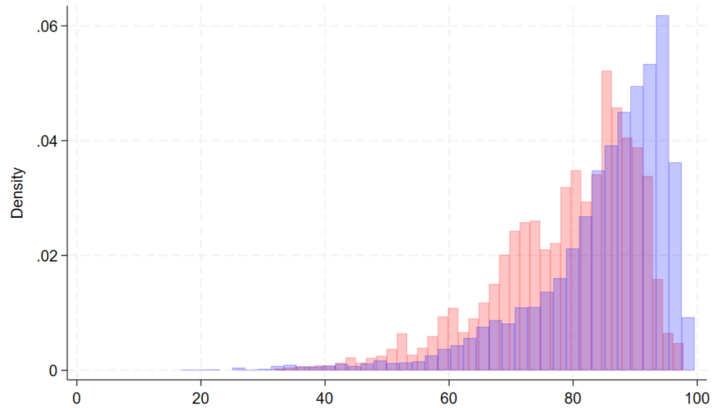
Although this alternative method eliminates the need to merge CoreLogic with HMDA data, it assumes that within each ZIP code, a racial group's share of purchases (sales) is directly proportional to its population. To assess the potential loss of precision caused by this assumption, we compare city-quarter-level purchase shares by race, $\frac{\text{Purchase}_{l,t,r}}{\sum_r \text{Purchase}_{l,t,r}}$, constructed using both our original method and the alternative method.

Figure 2 shows the distributions of purchase shares by race, constructed using the two methods. The alternative method overestimates the purchase shares for Black and Hispanic households. Specifically, with the alternative method, the average share of purchases made by Black households increases from 5.6% to 9.3%, and the average share of purchases made by Hispanic households rises from 9.7% to 11.9%. These differences in average purchase shares for a single racial group, constructed using two different methods, are statistically significant. They indicate that the propensity to purchase homes varies across racial groups even within the same ZIP code, with Black and Hispanic households less likely to purchase than White households.

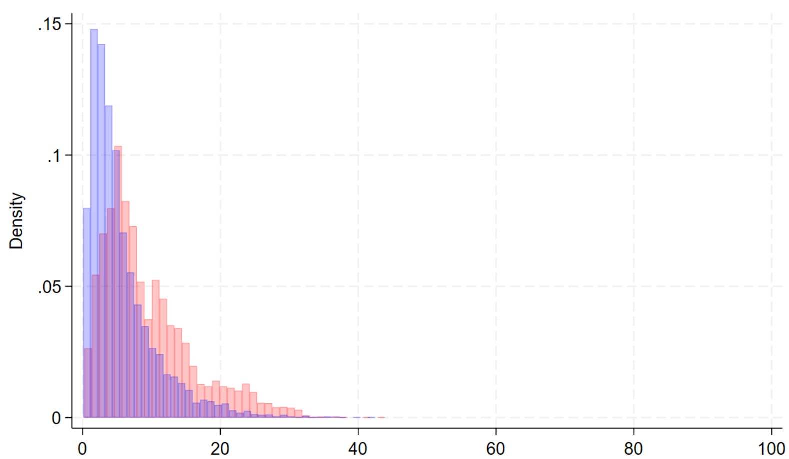
We also consider alternative methods of constructing race-specific HPIs. Zillow, for instance,

Figure 2: Comparison of the Alternative Method with the CoreLogic–HMDA Method: Purchase Share (Percent) Distribution

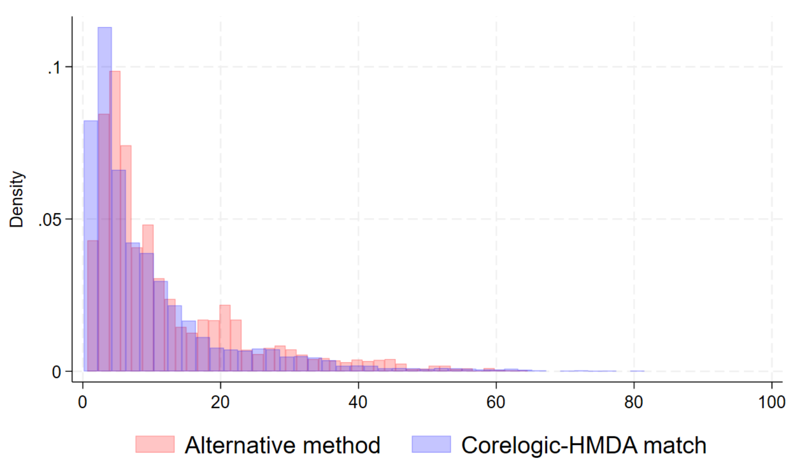
(a) White households



(b) Black households



(c) Hispanic households



developed the Zillow Home Value Index (ZHVI) by race without identifying the race of individual homeowners. Assuming that within a ZIP code, the dynamics of home price appreciation are identical across race groups, researchers from Zillow constructed the ZHVI by race using ZIP code-level (non-race-specific) ZHVI and ZIP code weights by race. The ZIP code weights by race are designed to reflect population and homeownership dynamics and are calculated using data on owner-occupied housing units by race from American Community Survey (ACS) five-year estimates.[15]

Our approach, which links CoreLogic with HMDA data, has several advantages over Zillow's method. First, our race-specific HPIs are not weighted averages of ZIP code HPIs, allowing us to capture within-ZIP code differences in home price appreciation by race. Second, our race-specific HPIs reach back to 1993, whereas Zillow's ZHVI by race relies on ACS data, which are only available from 2005 onward. Finally, we will make our race-specific HPIs publicly available, whereas ZHVI by race is not published by Zillow and is therefore unavailable to outside researchers.[16]

Despite our method's advantages, it is useful to compare our race-specific HPIs with ZHVI by race. Since Zillow does not publish the ZHVI by race data series, we rely on published research reports. One Zillow report reveals that from the peak in 2006 to the trough in 2011, home values for Black and Hispanic households declined by 8.7 and 22.6 percentage points more, respectively, compared to White households; from the trough to 2013, Black and Hispanic home values increased by -0.2 and 11.9 percentage points more, respectively, relative to White households.[17] Compared to Zillow's numbers, our estimate indicates less favorable housing cycles for Black and Hispanic households. According to our estimates, from 2006Q3 to 2011Q1, Black and Hispanic home values fell by 21.2 and 23.3 percentage points more, respectively; from 2011Q1 to 2013Q4, Black and Hispanic home values increased by -2.0 and 11.0 percentage points more, respectively. Despite the differences, the two sets of indices are qualitatively consistent: White households were the least affected by the housing bust, while Hispanic households, followed by Black households, were hit the hardest. However, Hispanic home values have recovered faster than Black home values.

We also construct HPIs by race using the Zillow methodology, but instead of ZHVI and ACS data, we use ZIP code-level HPIs from the FHFA and census data on ZIP code racial composition.[18] This approach allows us to extend the ZIP code-based race-specific HPIs back to 1995, enabling better comparison with our original race-specific HPIs. Let z represent a ZIP code. For each city l,

[15] See https://www.zillow.com/research/methodology-zhvi-by-race-2020-28525/.

[16] In principle, researchers could reconstruct race-specific HPIs by applying Zillow's methodology to the publicly available ZIP code-level ZHVI and ACS data.

[17] See https://www.zillow.com/research/BlackandHispanic-mortgage-access-6127/.

[18] We obtain the annual five-digit ZIP code FHFA HPI from https://www.fhfa.gov/data/hpi/datasets?tab=additional-data.

year t, and race r, we calculate the alternative measure of $\text{HPI}_{l,t,r}$ as $\sum_{z\in l}(\text{HPI}_{z,t} \times \frac{\text{population}_{z,t,r}}{\sum_{z\in l}\text{population}_{z,t,r}})$, where the summation over z covers all ZIP codes within city l.

To compare the race-specific HPIs yielded by this alternative method to our original HPIs, we merge the data constructed using the alternative approach with our final regression sample. Due to the incomplete ZIP code coverage in the FHFA data, the merged dataset represents only 48% of our final sample. As shown in Appendix Figure C.3, compared to our original method, the alternative method results in quarterly home price appreciation that are more centered around zero for all three racial groups.

2.3 Other Data

Race-specific labor market measures We obtain quarterly county-level employment and earnings statistics by race from the US Census Bureau's Quarterly Workforce Indicators (QWI) program.[19] QWIs are constructed from the Longitudinal Employer-Household Dynamics data and provide insights into the labor market dynamics of different racial groups. The variables we use are full-quarter employment (stable), end-of-quarter hiring rate, beginning-of-quarter separation rate, and average earnings. We aggregate the county-quarter level data to city-quarter level.[20]

To measure employment growth, we calculate the quarterly change in the logarithm of employment. In section 3.4, we investigate whether there are disparities in employment and earning dynamics across racial groups following monetary policy shocks that could potentially explain our findings about how racial housing disparities respond to monetary policy.

Unemployment rate We collect the monthly county-level unemployment rates from the US Bureau of Labor Statistics' Local Area Unemployment Statistics program. We then aggregate the data to quarterly city-level.

Racial composition To account for racial composition, we use county-year level population data by race and Hispanic origin from the National Bureau of Economic Research's Survey of Epidemiology and End Results data archive and aggregate it to the city-year level.[21] We then compute the Black population share and Hispanic population share for each city in each year.

[19] QWI data can be downloaded from https://www.census.gov/data/developers/data-sets/qwi.html.

[20] For the purpose of aggregation, we use the 2018 county-to-MSA crosswalk provided by the US Census Bureau, available athttps://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/historical-delineation-files.html.

[21] SEER data can be downloaded from https://www.nber.org/research/data/survey-epidemiology-and-end-results-seer-us-state-and-county-population-data-age-race-sex-hispanic

Lender concentration To capture the level of lender concentration, we adopt the approach used by Scharfstein and Sunderam (2013) to construct city-level lender concentration measures. These measures are based on the share of mortgages held by the top four lenders at the city-year level and are computed using HMDA microdata. Additionally, we compute the Herfindahl–Hirschman Index (HHI) as an alternative measure of lender concentration.

3 Empirical Framework and Findings

We present our empirical framework in section 3.1. We investigate the dynamic causal effect of monetary policy shocks on home purchases and sales in section 3.2 and on home price appreciation in section 3.3. We explore potential mechanisms in section 3.4 and present robustness checks in section 3.5.

3.1 Econometric Framework

Our econometric analysis uses the local projections (LPs) method introduced by Jordà (2005). To identify the causal effect of monetary policy, we use high-frequency monetary policy surprises as the external instrumental variable (IV).

As highlighted in Guren et al. (2021), there exists a significant interconnection between local housing and labor markets, making it essential to examine their joint dynamics. We investigate a dynamic system denoted as $[i_t, Y_{l,t}]$, where i_t represents the average federal funds rate in quarter t, and $Y_{l,t}$ is a vector of twelve variables consisting of net purchase intensity, home price appreciation, employment growth, and log of average earnings for the three racial groups in city l during quarter t.

By modeling the joint dynamics of local labor and housing market outcomes across the three racial groups, we account for the interaction among different racial groups in local business cycles.

Our specification is as follows,

$$y_{l,t+h} = \beta_y^{(h)} i_t + \text{controls} + \text{error}_{l,y,t}^{(h)}, \quad h = 0, 1, 2, \ldots, \tag{1}$$

where $y_{l,t}$ is one of the variables in $Y_{l,t}$ and the controls include four lagged values of $Y_{l,t}$ and i_t. The error term $\text{error}_{l,y,t}^{(h)}$ captures unobserved factors and random variation. This specification is a panel version of the lag-augmented local projections used in Montiel Olea and Plagborg-Møller (2021). The estimation of $\beta_y^{(h)}$ comes from the cross-sectional and temporal variations in the response of $y_{l,t+h}$ to monetary policy. City fixed effects are included in the model to control for unobserved heterogeneity across cities and to account for city-specific characteristics that may influence housing demand. The inclusion of fixed effects ensures the analysis focuses on within-city variations resulting from changes in monetary policy. We use the total population in each city as weight. Standard errors are clustered at the city level to account for potential correlations within the same city. In section 3.5, we perform robustness checks, including unweighted regressions and specifications without city fixed effects. We also explore a dynamic system denoted as $[\triangle i_t, Y_{l,t}]$, where $\triangle i_t$ represents the quarterly change in the federal funds rate, and confirm that the results remain robust.

Our empirical approach relies on using monetary policy surprises as an instrumental variable for i_t to address the endogeneity concern that arises when policy interest rates are set by central banks in response to macroeconomic variables. For example, the Fed might reduce interest rates to counteract weakening labor markets. In such cases, the impact of the Fed's actions is confounded by labor market conditions, making it challenging to isolate the true effects of monetary policy.

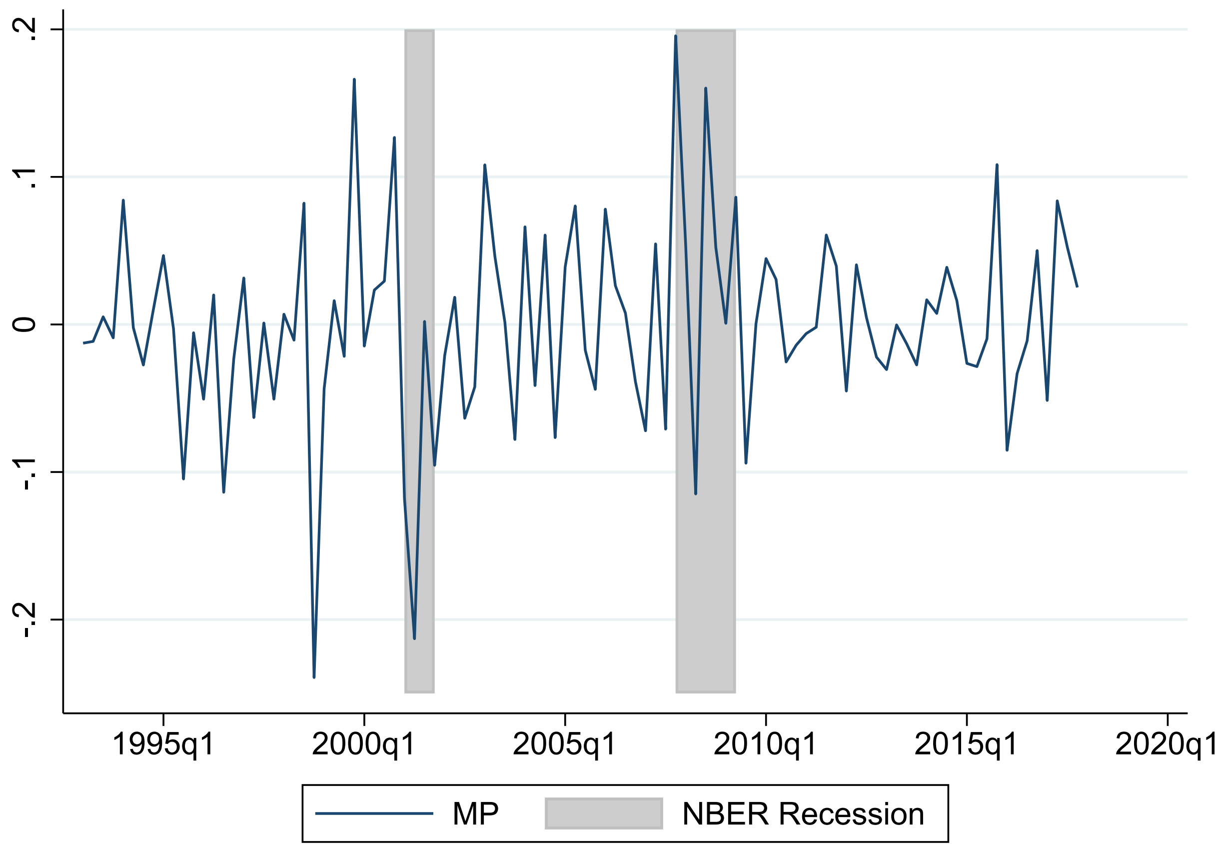
Over the past two decades, monetary policy surprises have become essential for studying the effects of monetary policy on asset prices and the broader economy. This strategy is grounded in the pioneering literature of Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2005) and Gürkaynak et al. (2005), which utilizes the timing of Federal Open Market Committee (FOMC) decisions to identify monetary policy surprises from changes in asset prices around FOMC announcements. By focusing on high-frequency changes in asset prices – specifically, changes that occur 10 minutes before and 20 minutes after an FOMC announcement – this method offers two key advantages. First, any non-monetary shocks known at the start of the 30-minute window are already priced into the markets, preventing them from distorting the measurement of monetary policy surprises. Second, changes in asset prices within this narrow window are primarily driven by new information about future monetary policy revealed in FOMC announcements.

To ensure relevance, rates on financial assets with direct linkage to policy decisions, such as federal funds futures and Eurodollar futures, are often used to construct monetary policy surprises. Federal funds futures settle based on the 30-day average of the federal funds rate, while Eurodollar futures settle based on the three-month London interbank offered rate at expiration. These assets are highly sensitive to the federal funds rate and its near-future path. For example, the second through fourth Eurodollar futures contracts reflect market expectations regarding the federal funds rate path over a horizon of roughly 5 to 14 months ahead (Swanson, 2021).

In our baseline analysis, we use the monetary policy surprises recently developed by Bauer and Swanson (2023), which cover our sample period from 1995 to 2017. These surprises are derived from high-frequency asset price changes, but the authors have also purged them, making them plausibly exogenous to all macroeconomic variables publicly known before the FOMC decisions are made. Consequently, they serve as valid instruments for studying the causal effects of monetary policy.

The monetary policy surprise series are normalized such that a 25-basis-point increase in the surprise corresponds to a 25-basis-point increase in the intraday movements of the fourth quarterly Eurodollar futures (ED4) rate.[22] Positive values of the surprise indicate a contractionary monetary policy stance. Further details on the impact of surprises on various financial assets can be found in Appendix D. We aggregate all FOMC meeting-level monetary policy surprises within each quarter. This aggregation relies on the assumption that these surprises are orthogonal to economic variables in a quarter. The resulting quarterly monetary policy surprise series are visualized in Figure 3.

Figure 3: Monetary Policy Surprises at Quarterly Frequency



Notes: This figure plots the quarterly series of monetary policy surprises. The surprises are first computed at FOMC meeting frequency, where a 25-basis-point increase in the surprises corresponds to a 25-basis-point increase in the fourth quarterly Eurodollar future (ED4) rate. To derive the quarterly monetary policy surprises, we aggregate all meeting-level surprises within each quarter. Positive values correspond to contractionary monetary policy surprises.

We test whether monetary policy surprises are a strong instrument for the federal funds rate.

[22]Quarterly Eurodollar futures expire on the International Monetary Market dates: the third Wednesday of March, June, September, and December. Eurodollar futures settle based on the spot 90-day Eurodollar deposit rate at expiration. The fourth Eurodollar futures contract can have as little as three quarters plus one day to expiration and as much as four quarters to expiration. Its rate is related to federal funds rate expectations 3.5 – 4.5 quarters ahead (Gürkaynak et al., 2005).

The Cragg-Donald Wald F statistics for the regressions in sections 3.2 and 3.3 range from 179 to 338 for horizons of 0 to 20 quarters.[23] These results firmly reject the null hypothesis of a weak instrument.

To ensure the robustness of our results, we repeat our analysis using alternative measures of monetary policy surprises. Specifically, we use the first principal component of the high-frequency asset price changes mentioned above without purging. In addition, we perform several other robustness checks. For example, following Eichenbaum et al. (2022), we include various additional observable measures as controls, such as city-level population share by race, unemployment rate, and lender competitiveness, and find that the results remain largely unchanged. The details of these robustness checks are outlined in the section 3.5.

3.2 Home Purchases and Sales

First, we focus on the effects of monetary policy on net purchase intensity, as measured by log(purchase/sale). Our measures of home purchases and sales have two limitations. First, our measure of home purchases includes both entries into homeownership, upgrades, and purchases of second homes. Likewise, our measure of home sales includes both exits from homeownership, downgrades, and sales of second homes. Measuring entry into and exit from homeownership requires us to track individual market participants across properties and time, which we cannot do with high confidence due to the limited individual-level information available in the CoreLogic–HMDA data. Second, since we rely on HMDA data to identify the race of homeowners, our measures of home purchases and sales necessarily exclude all cash transactions. We believe that despite these limitations, our analysis of home purchases and sales provides a broad view of how monetary policy affects racial disparities in housing. In section 4, we present additional findings to address these limitations.

Appendix Figure E.1a displays the impulse response of the net purchase intensity to a 25-basis-point increase in the federal funds rate by race. We present the point estimates and confidence intervals for the coefficient of $0.25 \times \beta_y^{(h)}$ in equation (1), where y encompasses the net purchase intensity for White, Black, and Hispanic households. In Figure 4a of the main text, however, in addition to presenting, in the left panel, the impulse response of White households, $0.25 \times \beta^{(h)}_{\text{net purchase, white}}$, we present, in the right panel, the differences in impulse responses between Black and White households, $0.25 \times (\beta^{(h)}_{\text{net purchase,black}} - \beta^{(h)}_{\text{net purchase,white}})$, denoted by a solid red line, and the differences in impulse responses between Hispanic and White households, $0.25 \times (\beta^{(h)}_{\text{net purchase,hispanic}} - \beta^{(h)}_{\text{net purchase,white}})$, denoted by a dashed blue line. This is because our focus is on the difference across racial groups and whether it is significantly different from zero.

[23] Due to the unbalanced nature of the data, some variations in the F statistics are observed.

We construct confidence intervals and perform statistical tests to evaluate the significance of these differences.[24]

As illustrated in Figure 4a, following contractionary monetary policy, the net purchase intensity for White households generally increases. In contrast, the net purchase intensities for Black and Hispanic households decline relative to White households, dropping by approximately 6 and 7 percentage points more, respectively, after two quarters, and by about 12.6 and 16.9 percentage points more, respectively, after sixteen quarters.

In the left panels of Figures 5a and 5b, we present the regression results for home purchases and sales separately for White households. Our analysis reveals that, following contractionary monetary policy, gross purchases generally increase for White households, while gross sales generally decrease. Both factors contribute to the rise in net purchase intensity for White households. In the right panels of Figures 5a and 5b, we plot the difference in responses of Black households (solid red line) and Hispanic households (dashed blue line) from White households. We first focus on the very short-term impact of monetary policy. The right panel of Figure 5a indicates that the home purchases of Black and Hispanic households do not differ significantly from those of White households two quarters following a contractionary monetary policy shock. The right panel of Figure 5b reveals that during this time, Black and Hispanic households increase their home sales by 2.3 and 5 percentage points more, respectively, relative to White households. Therefore, the

[24] Let $\mathfrak{Y}$ represent one of the following metrics of housing markets and labor markets: net purchase intensity, home price appreciation, employment growth, or log of average earnings. For illustrative purposes and without loss of generality, we use a univariate $x_{l,t-1}$ to represent the control variables in equation (1), though our full set of controls encompasses four lagged values of $Y_{l,t}$, four lagged values of i_t and city fixed effects. To examine the impulse response of $\mathfrak{Y}$ by race, we estimate equation (1) separately for White, Black, and Hispanic, with the dependent variable $y_{l,t+h}$ being $\mathfrak{Y}_{white,l,t+h}$, $\mathfrak{Y}_{black,l,t+h}$, and $\mathfrak{Y}_{hispanic,l,t+h}$, respectively.

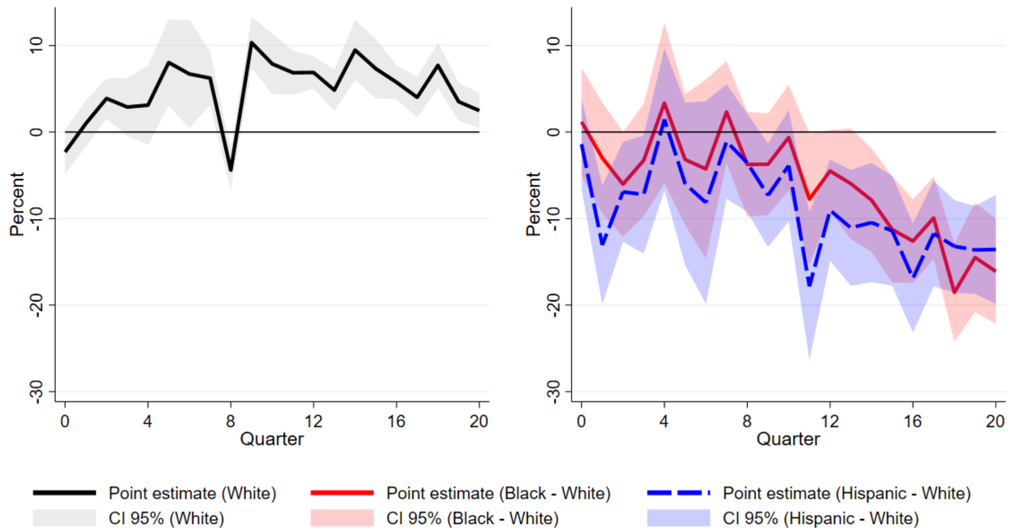
$$\begin{aligned}
\mathfrak{Y}_{white,l,t+h} &= \beta^{(h)}_{\mathfrak{Y},white} i_t + \alpha^{(h)}_{\mathfrak{Y},white} x_{l,t-1} + \text{error}^{(h)}_{l,\mathfrak{Y},white,t} \\
\mathfrak{Y}_{black,l,t+h} &= \beta^{(h)}_{\mathfrak{Y},black} i_t + \alpha^{(h)}_{\mathfrak{Y},black} x_{l,t-1} + \text{error}^{(h)}_{l,\mathfrak{Y},black,t} \\
\mathfrak{Y}_{hispanic,l,t+h} &= \beta^{(h)}_{\mathfrak{Y},hispanic} i_t + \alpha^{(h)}_{\mathfrak{Y},hispanic} x_{l,t-1} + \text{error}^{(h)}_{l,\mathfrak{Y},hispanic,t}
\end{aligned}$$

To estimate the differences in impulse responses by race, we append the data from three racial groups and rearrange the equations in the following form. We then estimate the new system and test the coefficients.

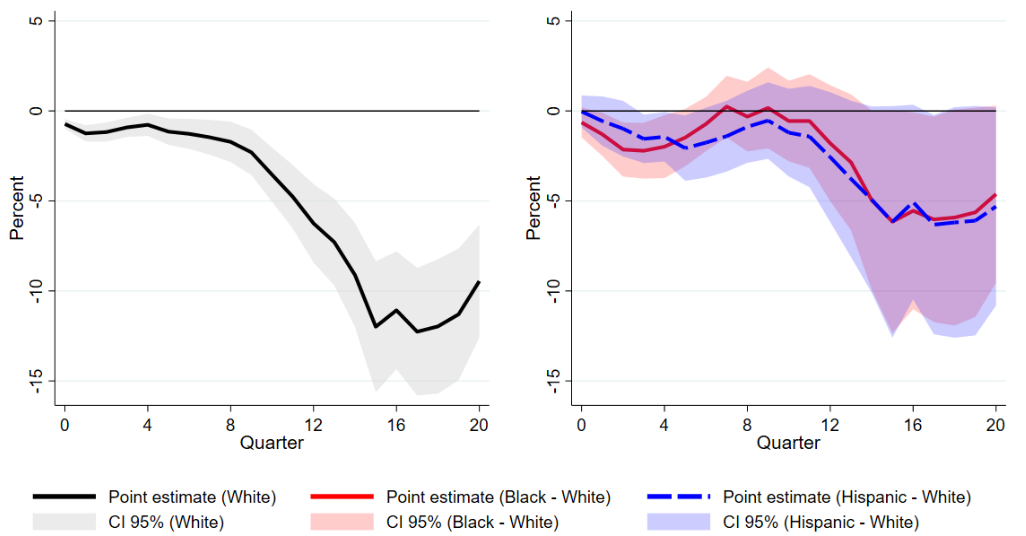
$$\begin{aligned}
\begin{bmatrix} \mathfrak{Y}_{\text{white},l,t+h} \\ \mathfrak{Y}_{\text{black},l,t+h} \\ \mathfrak{Y}_{\text{hispanic},l,t+h} \end{bmatrix} = &\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \beta^{(h)}_{\mathfrak{Y},white} i_t + \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} (\beta^{(h)}_{\mathfrak{Y},black} - \beta^{(h)}_{\mathfrak{Y},white}) i_t + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} (\beta^{(h)}_{\mathfrak{Y},hispanic} - \beta^{(h)}_{\mathfrak{Y},white}) i_t \\
&+ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \alpha^{(h)}_{\mathfrak{Y},white} x_{l,t-1} + \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} (\alpha^{(h)}_{\mathfrak{Y},black} - \alpha^{(h)}_{\mathfrak{Y},white}) x_{l,t-1} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} (\alpha^{(h)}_{\mathfrak{Y},hispanic} - \alpha^{(h)}_{\mathfrak{Y},white}) x_{l,t-1} \\
&+ \begin{bmatrix} \text{error}^{(h)}_{l,\mathfrak{Y},white,t} \\ \text{error}^{(h)}_{l,\mathfrak{Y},black,t} \\ \text{error}^{(h)}_{l,\mathfrak{Y},hispanic,t} \end{bmatrix}, \quad h = 0, 1, 2, \ldots
\end{aligned}$$

Figure 4: Responses of Net Purchase Intensity and Home Price to Monetary Policy by Race

(a) Net purchase intensity



(b) Home price

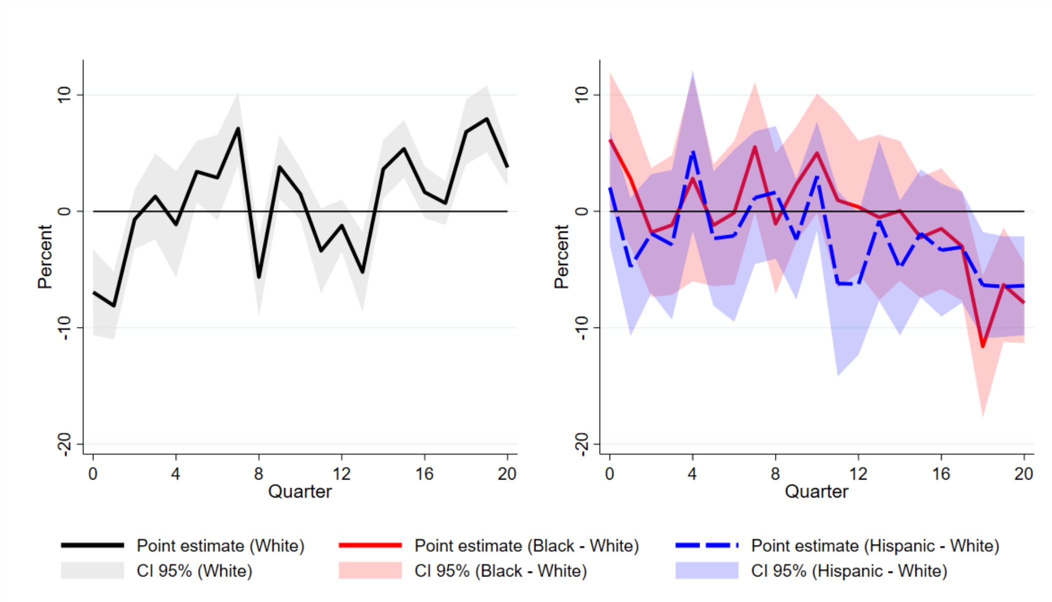


Notes: Panels (a) and (b) present the responses of the net purchase intensity and cumulative (log) home price change to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

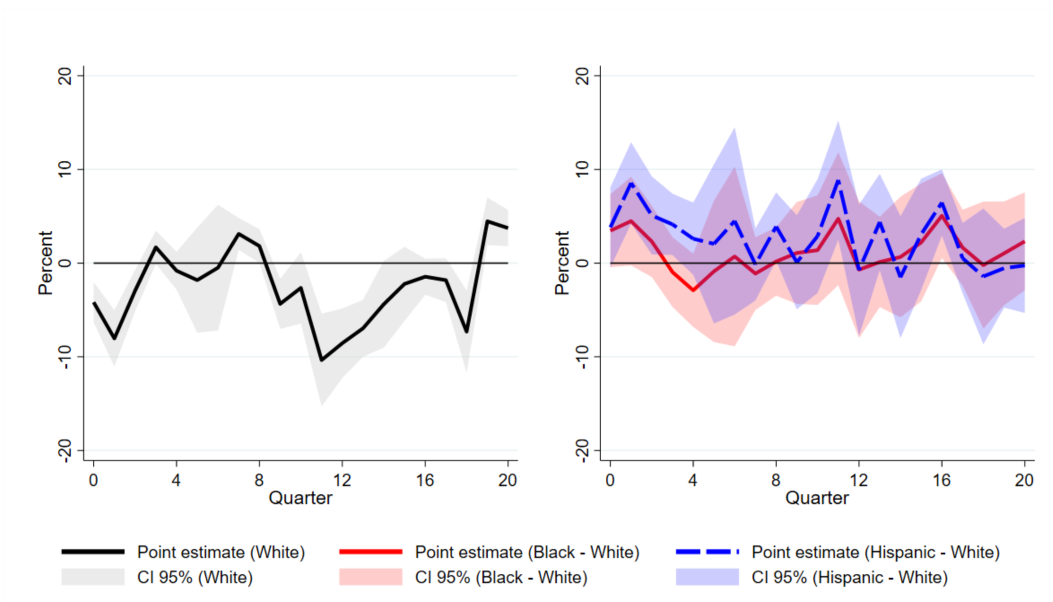
initial relative declines in net purchases observed in the right panel of Figure 4a are caused by the gross sale margin. Next, we look at sixteen quarters after a contractionary monetary shock. The right panel of Figure 5a shows that Black and Hispanic households reduce their home purchases by approximately 1.5 and 3.3 percentage points more than White households, respectively, while the right panel of Figure 5b reveals that they increase their home sales by 5 and 6.5 percentage points more than White households, respectively. These relative reductions in home purchases and increases in sales jointly account for the diminished net purchase intensities of Black and Hispanic households compared to White households following monetary tightening.

Figure 5: Responses of Gross Purchase and Gross Sale to Monetary Policy by Race

(a) Gross purchase



(b) Gross sale



Notes: Panels (a) and (b) present the responses of (log) gross purchases and (log) gross sales to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

3.3 Home Price Appreciation

Thus far, we have documented that monetary tightening disproportionately affects net home purchases of Black and Hispanic households. In this subsection, we examine whether monetary tightening also disproportionately affects the home price appreciation for Black and Hispanic homeowners.

In Figure 4b, we plot the effect of a 25-basis-point increase in the federal funds rate on cumulative home price appreciation. The left panel illustrates that contractionary monetary policy shocks have negative impacts on home prices for White homeowners. The right panel shows significant variations in the dynamics of home prices across racial groups. Following a 25-basis-point increase in the policy rate, the average home price for White households drops by 0.8 percent within 4 quarters, compared to the counterfactual scenario without the monetary policy shock. The average home prices for Black and Hispanic households decrease by an additional 2 and 1.4 percentage points, respectively, during the same period. At the 16-quarter mark, the disparities across racial groups become even more pronounced. Black and Hispanic households experience an additional decline in home prices of 5.5 and 5 percentage points, respectively, compared to White households within the same time frame. In section 4.4, we perform the same analysis using foreclosure-free HPIs, and the results are very similar.

We look at the effect of monetary policy not only on nominal home prices but also on real home prices. Our analysis indicates that two years after a 25-basis-point policy rate increase, White households experience a decrease in real house prices of 1.9 percent, with a 95 percent confidence interval from 0.7 to 3 percent. This is consistent with Williams (2016) who examined five papers using the US data and found that, on average, there is a 1.75 percent decrease in real house prices over a two-year period following a 25-basis-point exogenous increase in the short-term interest rate. The magnitude of the decrease ranges from 0.43 to 2.7 percent. Additionally, we find that sixteen quarters after the monetary policy shock, Black and Hispanic households experience additional real home price depreciation of 5 and 4.7 percentage points, respectively, compared to White households. These results provide valuable insights into the differential impacts of monetary policy on home prices across racial groups. Further details can be found in section 3.5.

3.4 Potential Mechanisms

The results so far indicate that contractionary monetary shocks lead to a relative reduction in net home purchases by Black and Hispanic households, along with greater home price depreciation for these groups. These findings prompt a deeper inquiry: what mechanisms contribute to the exacerbation of housing disparities between Black and White, or Hispanic and White households after monetary tightening? In this subsection, we explore two important channels through which monetary shocks may be transmitted to the housing market: the labor market channel and the financing channel. By investigating these channels, we offer insights into how monetary policy affects the housing market and why these effects differ across racial groups.

One important channel through which monetary policy affects the housing market is employment. An individual needs a stable job to apply for a mortgage (Munnell et al., 1996). Typically, receiving mortgage approval necessitates a work history spanning at least two years. If a person is currently unemployed or has a job duration shorter than 2 years, his/her mortgage application is usually subject to more scrutiny.[25] Monetary tightening can lead to declines in aggregate demand and reductions in job vacancies. This, in turn, may result in unemployment or shorter job duration, which discourages or may even disqualify people from purchasing homes. The employment channel may explain why the housing market outcomes of Black and Hispanic workers are more responsive to monetary shocks than those of White workers, if the labor market outcomes of Black and Hispanic workers are also more responsive. Thus, in what follows, we analyze the evolution of labor market outcomes by racial group after a monetary policy shock.

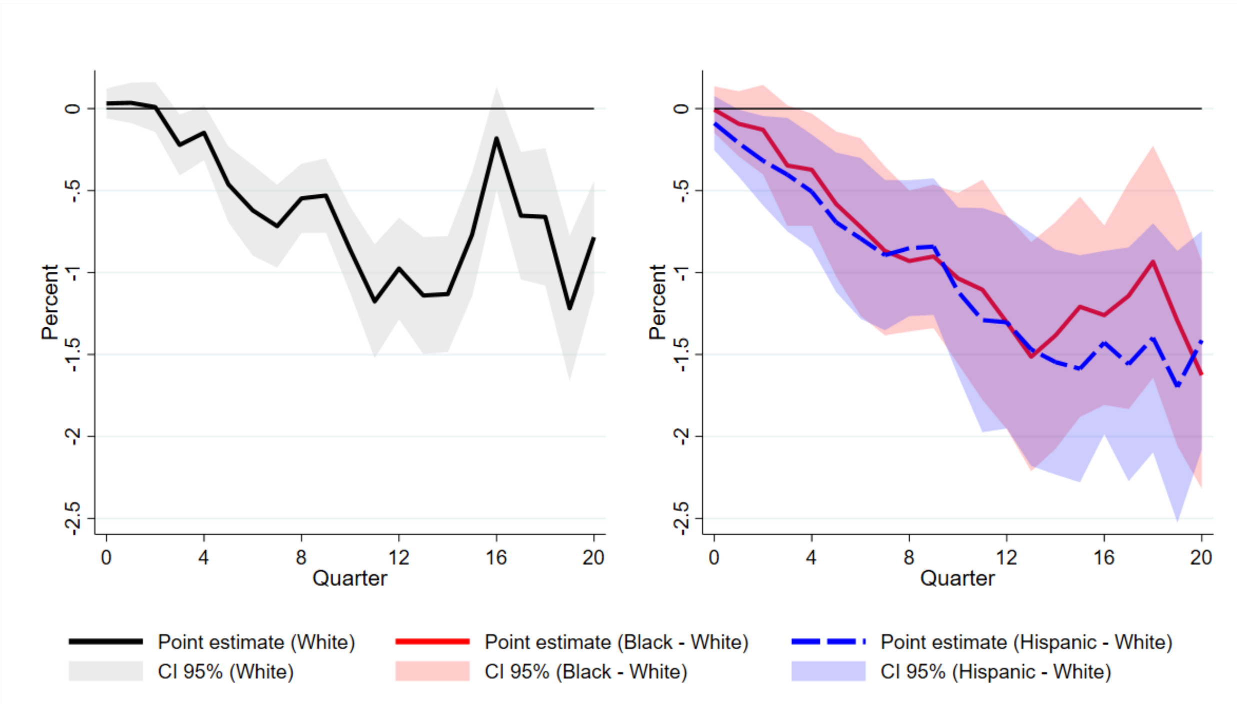
Our empirical approach allows us to identify the overall effects of monetary policy on employment by race. The left panel of Figure 6 presents the impact of a 25-basis-point increase in the federal funds rate on the cumulative employment growth for White workers. The employment for White workers decreases by 0.15 percent in 4 quarters and by 0.5 percent in 8 quarters. The right panel reveals that employment among Black and Hispanic workers declines significantly more than among White workers. After four quarters, the cumulative decline in employment growth for Black and for Hispanic workers is 0.4 and 0.5 percentage points greater than for White workers, respectively. This disparity widens over eight quarters, with declines of 0.9 percentage points for both Black and Hispanic workers compared to their White counterparts. After sixteen quarters, the cumulative additional decline is 1.3 percentage points greater for Black workers and 1.4 percentage points greater for Hispanic workers.

Overall, our findings suggest that the negative impact of contractionary monetary policy on employment is more pronounced for Black and Hispanic workers than for their White counterparts. These findings broadly align with those of Bergman et al. (2022), which shows that, conditioning on tight labor markets, the employment growth of Black workers is more responsive to monetary policy. While Bergman et al. (2022) provides valuable insights by focusing on employment growth of disadvantaged groups conditional on tight labor markets, our study complements and advances this line of inquiry by considering the unconditional effects of monetary policy and incorporating

[25]FHA loan approval requires borrower to have steady income and proof of employment (source: https://www.fha.com/fha_loan_requirements). In fact, most lenders require stable employment for borrowers; see, e.g., https://mfmbankers.com/job-changes-and-other-factors-that-affect-the-home-buying-process/.

additional economic variables, such as earnings and housing market dynamics. By modeling the joint dynamics of local labor and housing market outcomes, we are able to capture the important interplay between these markets, as recently emphasized by Guren et al. (2021). Furthermore, while Bergman et al. (2022) analyzes each racial group separately without controlling for the outcomes of other racial groups, our analysis includes the housing, earning, and employment variables across three racial groups. This approach allows us to account for the interactions between different racial groups within local business cycles.

Figure 6: Response of Employment to Monetary Policy by Race



Notes: This figure presents the responses of cumulative employment growth to a 25-basis-point increase in the federal funds rate. The impulse response of White households is presented on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Next, we deepen our analysis by examining employment adjustments across two margins: hiring and separation. We measure these margins using the end-of-quarter hiring rate and the beginning-of-quarter separation rate. These metrics, along with quarterly home price appreciation, net purchase intensity, and log of average earnings, are integrated into the local projection framework. The results are shown in Figures 7a and 7b. Our findings reveal that, following a contractionary monetary policy shock, both the hiring and separation rates decline more for Black and Hispanic workers than they do for White workers. However, the relative decline in the hiring rate for Black and Hispanic workers outweighs the relative decline in their separation rate, leading to a relative decrease in employment for these groups.

In addition to exploring employment, we investigate another critical aspect of the labor market: average earnings. Figure 8a focuses on the effects of a 25-basis-point increase in the federal funds rate on the log of average earnings for different racial groups. In contrast to the employment results, the average earnings results show minimal disparities between Black, Hispanic, and White workers.

Changes in mortgage interest rates represent a direct transmission mechanism through which monetary policy influences the housing market. Lower mortgage interest rates reduce the cost of borrowing for home buyers, making mortgages more affordable. This may incentivize individuals to purchase homes, thus increasing home prices. If the pass-through of the policy rate to mortgage interest rates is stronger for Black and Hispanic households than it is for White households, this financing channel may explain why housing market outcomes of Black and Hispanic households are more responsive to monetary shocks than those of White households. Thus, in what follows, we analyze the evolution of mortgage interest rates by racial group after a monetary shock.

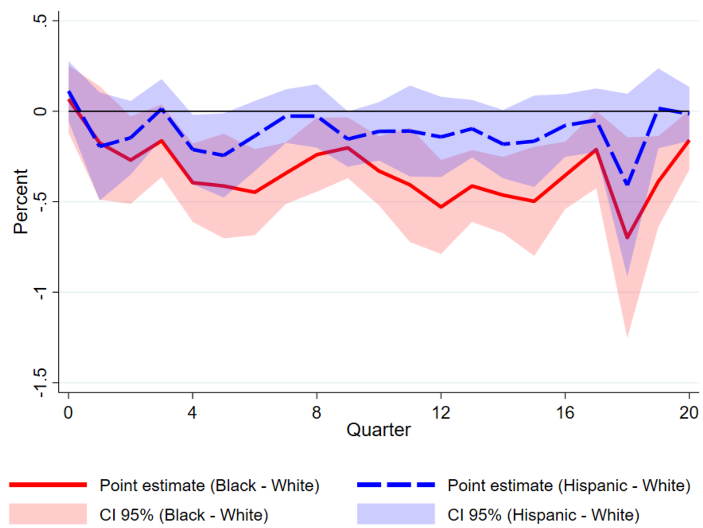
To test whether the pass-through of monetary policy differs by race, we used the CoreLogic–HMDA data to obtain average interest rates on 30-year conventional purchase mortgages by city, quarter, and race. We then employ local projections to examine the responses of race-specific average mortgage rates to monetary policy shocks by including the average mortgage rates of the three racial groups in our regression specification (1). Since average mortgage rates have fewer observations than our other variables, we control for two lags of the following variables: average mortgage rates, net purchase intensity, home price appreciation, employment growth, and log earnings, for all three racial groups.

The left panel of Figure 8b shows the responses of average mortgage rate for White households, while the right panel of Figure 8b shows the responses for Black and Hispanic households relative to White households. Notably, our analysis reveals minimal differences in the pass-through of monetary policy by race, which discounts the role of the financing channel in explaining the excess responsiveness of housing market outcomes for Black and Hispanic households to monetary policy. While our data are quite comprehensive, they may nevertheless be insufficient to capture any significant racial differences in the financing channel. Further investigation using alternative data sources such as rate lock data may provide more comprehensive insights into the potential racial disparities in monetary policy pass-through to mortgage rates.

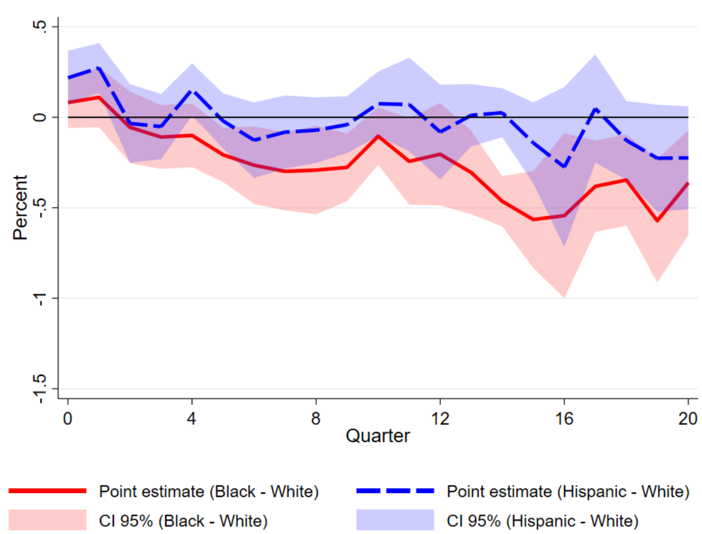
Overall, our analysis suggests that racial groups' heterogeneous responses in employment, rather than differences in interest rate pass-through, explain why Black and Hispanic households' home purchases and home prices are more sensitive to monetary policy than those of White households. This finding implies that the labor market may be an important channel in shaping housing market dynamics for Black and Hispanic groups in response to monetary policy changes. Of course, other factors may also contribute to the observed heterogeneous response. For example, racial differences in the mortgage approval rate, the propensity to prepay or refinance mortgages, the take-up of adjustable rate mortgages, and non-interest financing costs may also influence racial groups' housing market responses to monetary policy. An examination of these factors would yield a more comprehensive understanding of housing market dynamics and help further explain the observed racial heterogeneity in responses to monetary policy. We leave these areas for future research.

Figure 7: Responses of Hiring and Separation to Monetary Policy by Race

(a) Hiring rate



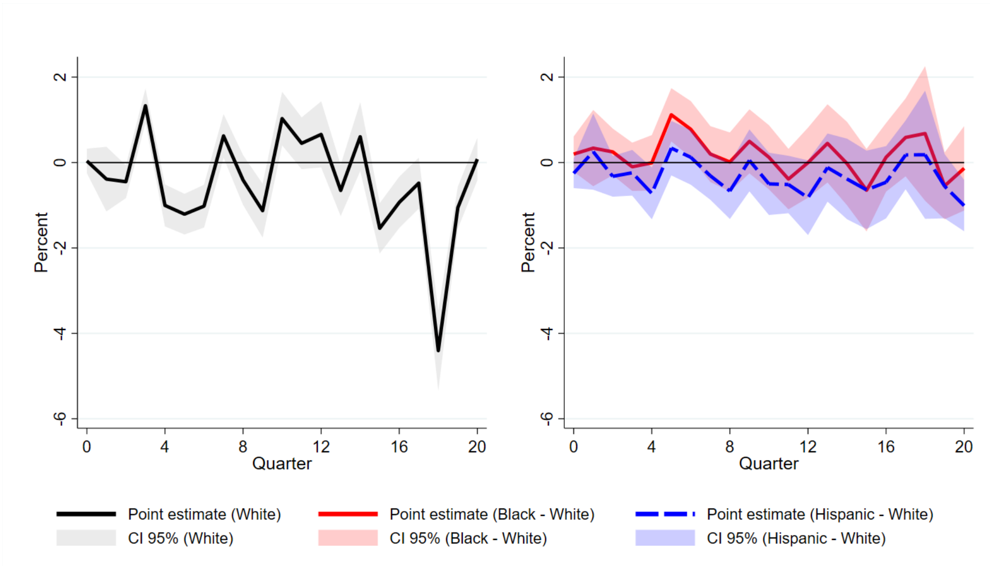
(b) Separation rate



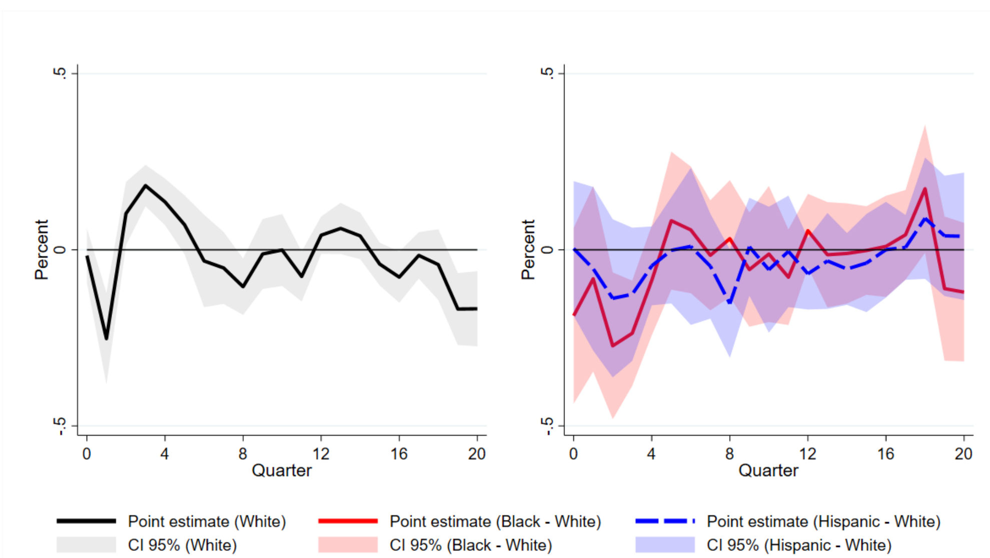
Notes: Panels (a) and (b) present the responses of hiring and separation rates to a 25-basis-point increase in the federal funds rate, respectively. The differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Figure 8: Responses of Average Earnings and Average Mortgage Rates to Monetary Policy by Race

(a) Average earnings



(b) Average mortgage rates



Notes: Panels (a) and (b) present the responses of (log) average earnings and average mortgage rates to a 25-basis-point increase in the federal funds rate, respectively. The differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

3.5 Robustness Checks

To ensure the robustness of our baseline results, we conduct ten different robustness checks. These include using an alternative instrumental variable for monetary policy, measuring net purchase intensity by focusing on dollar volumes of purchases and sales rather than counts, evaluating the impact on real home price appreciation, and testing an alternative specification incorporating quarterly changes in the federal funds rate, $\triangle i_t$. We also introduce additional controls to account for potential confounding factors, assess the results without city fixed effects, and add more variable lags. Moreover, we analyze unweighted results to validate our findings under different weighting assumptions and employ a reduced-form specification. These extensive checks confirm the robustness of our findings.

Alternative instrument for monetary policy We consider an alternative instrument for monetary policy. Following Nakamura and Steinsson (2018), we use the first principal component of interest rate changes in the current month federal funds futures (adjusted by the number of days that remain in the month relative to the total number of days), the three-month-ahead federal funds futures, the second, third, and fourth Eurodollar futures (ED2, ED3, ED4), measured within 30-minute windows surrounding FOMC announcements. We rescale this principal component so that a 25-basis-point increase in the level of the principal component corresponds to a 25-basis-point increase in the ED4 rate. This new series of monetary policy surprises is then aggregated at a quarterly frequency. When we repeat our baseline analysis using this alternative instrument for the federal funds rate, our results remain robust, as shown in Figure 9.

Net purchase volume intensity Our baseline specification uses a count-based measure of net purchase intensity, defined as the (log of) the number of purchases over the number of sales. Additionally, we construct a volume-based measure where net purchase volume intensity is calculated as the (log of) purchase dollar volume over sale dollar volume. This volume-based measure not only captures the extensive margin of housing transactions but also the intensive margin, thereby indicating whether the transactions involve higher-quality houses. The results, shown in Figure F.1, confirm that our baseline findings are robust when considering the quality of houses in addition to the quantity.

Real HPI We check the robustness of our findings to the use of real home prices by deflating nominal HPIs using the national Consumer Price Index. The results, displayed in Figure F.2, reveal that two quarters after a 25-basis-point monetary policy tightening, White households experience a 1.3 percent cumulative decrease in real house price compared to the counterfactual scenario without the monetary policy shock. Black and Hispanic households face additional declines of 1.7 and

3.2 percentage points, respectively, beyond the decrease observed for White households. Furthermore, sixteen quarters after the monetary policy shock, Black and Hispanic households encounter additional real home price depreciation of 5 percent and 4.7 percentage points, respectively, compared to White households.

Alternative specification with $\triangle i_t$ In our main specification, we use the level of the federal funds rate and control for its four lags. Alternatively, we use the change in the federal funds rate, $\triangle i_t$, without lags. We investigate a dynamic system denoted as $[\triangle i_t, Y_{l,t}]$. We use high-frequency monetary policy surprises as the external instrumental variable for $\triangle i_t$. The results are robust and consistent with our main findings, as shown in Figure F.3.

Additional control variables To account for city-level demographic influences, we incorporate the Black population share and Hispanic population share as additional control variables. This addresses the impact of minority inflows and outflows on housing demand. Additionally, we include city-level unemployment rates to capture the economic conditions affecting housing demand beyond employment and average earnings by race. Furthermore, we follow Eichenbaum et al. (2022) and include the lender competitiveness, which can affect housing demand indirectly via the degree of interest rate pass-through. Our results, displayed in Figure F.4, remain the same with these additional controls. Moreover, we use CoreLogic data to compute the share of FHA mortgages and the average LTV ratio at the city-quarter-race level. Including these variables, along with those previously mentioned, as additional controls in our analysis, does not change our results, as shown in Figure F.5.

Potential estimator bias Recent research including Herbst and Johannsen (2024) shows that the local projection estimator can be biased in small samples. Another potential bias in the panel data regressions, which is discussed in Nickell (1981), arises from including the lag of the dependent variable as a control and using fixed effects. Notably, both biases do not diminish as the number of entities increases. However, with a larger time dimension and less persistent data—such as quarterly rather than daily data—the bias becomes negligible. In our study, the potential bias of the local projections method with fixed effects is not a concern because we have nearly 100 time periods and our data is at a quarterly frequency, making it less persistent. Additionally, to address the Nickell bias in the dynamic fixed effect model, we show that our results are robust to excluding fixed effects from the regression model in Figure F.6.

Standard error We also consider heteroskedastic and autocorrelation consistent (HAC) standard errors. As shown in Figure F.7, our results are robust under these specifications.

Time variation We test whether the identified relationships are sensitive to the time period chosen. As mentioned earlier, a longer time dimension is necessary to minimize bias in the estimates. Therefore, we cannot re-estimate the baseline results using very short samples. In Figures F.8 and F.9, we restrict our sample to 1995–2013 and 2000–2017, respectively. In Figure F.10, we exclude the years 2008 and 2009. Across all these different time periods, our results remain robust.

Weights We use population weights in our baseline regressions. To ensure robustness, we also conduct the analysis without weighting the observations. As illustrated in Figure F.11, our findings remain robust.

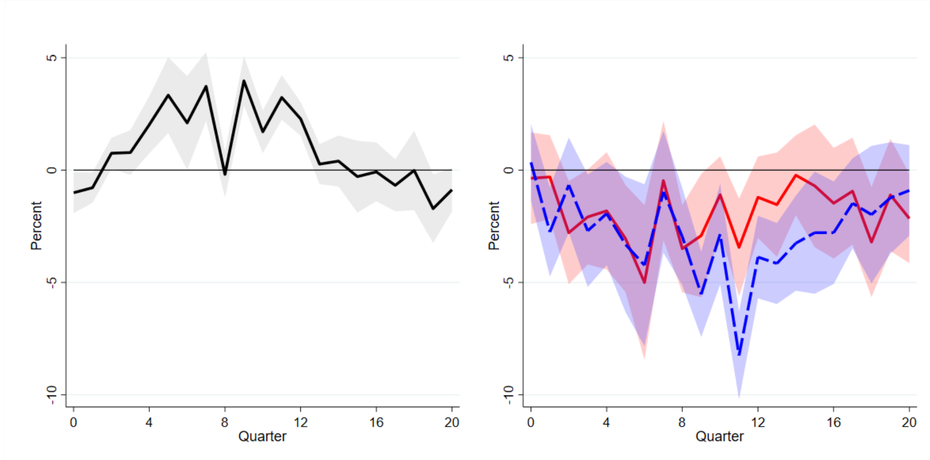
Reduced form Finally, our baseline findings use an LP-IV framework. We re-run the regressions using reduced-form LP-ordinary least squares (OLS),

$$\mathrm{y}_{l,t+h} = \alpha_y^{(h)} \mathrm{MP}_t + \text{controls} + \text{error}_{l,y,t}^{(h)}, \quad h = 0, 1, 2, \dots, \tag{2}$$

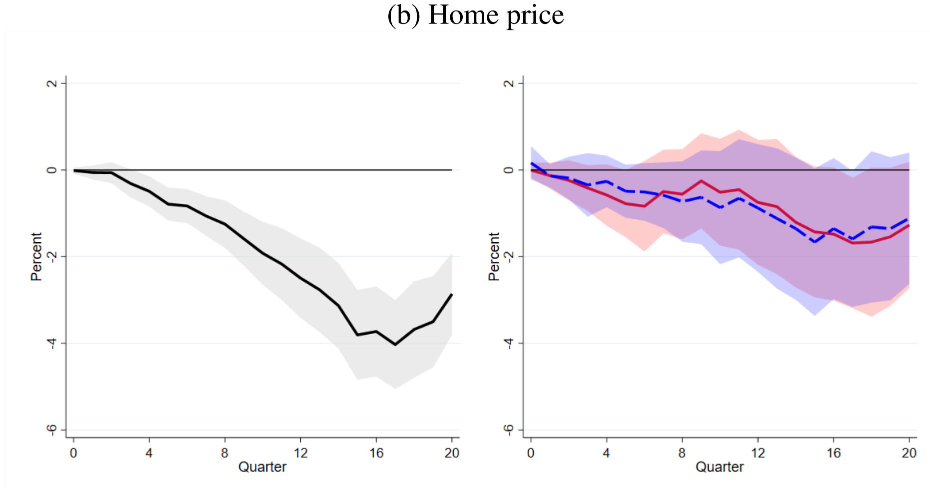
where $y_{l,t}$ is one of the variables in $Y_{l,t}$; MP_t is the observed monetary policy surprise, which is normalized such that a 25-basis-point increase in the surprise corresponds to a 25-basis-point increase in the intraday fluctuations of the fourth quarterly Eurodollar future rate; and controls encompass four lagged values of $Y_{l,t}$, four lagged values of MP_t and city fixed effects. The error term $\text{error}_{l,y,t}^{(h)}$ captures unobserved factors and random variation. The findings, presented in Figure F.12, remain robust in both qualitative and quantitative terms.

Figure 9: Responses to Monetary Policy by Race, Alternative IV

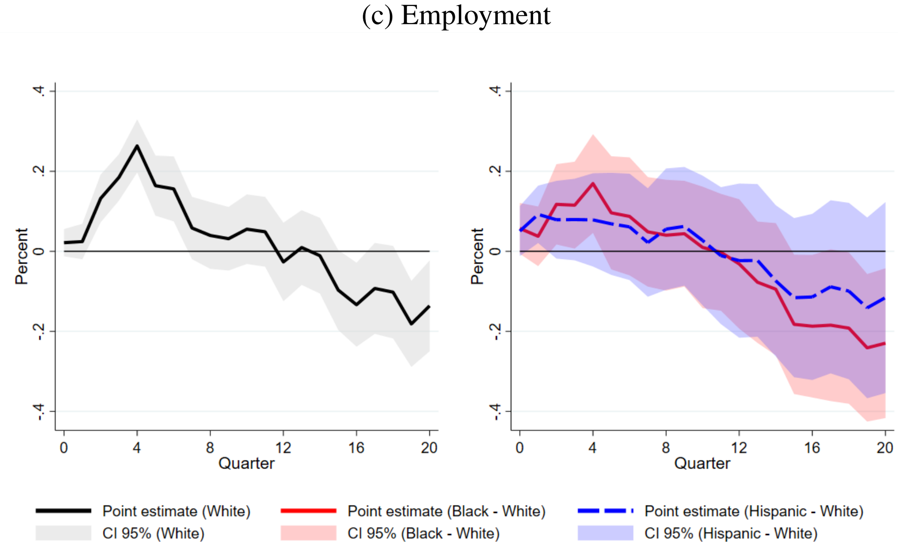
(a) Net purchase intensity



(b) Home price



(c) Employment



Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. We use an alternative measure of monetary policy surprises as the instrument for monetary policy. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

4 Discussion

In this section, we present extensions of our baseline results. We examine the role of residential segregation in section 4.1. Next, we explore the substitution between cash and mortgage purchases in section 4.2. In section 4.3, we use FHA loans to proxy for entries into homeownership. The role of foreclosure is discussed in section 4.4. We also analyze the effect of monetary policy on race-specific housing metrics by income in section 4.5. Finally, we investigate the asymmetric effects of monetary policy in section 4.6.

4.1 Effects of residential segregation

Our results indicate that home price appreciation following monetary shocks varies by race. What might explain this observed racial disparity in home price appreciation after a monetary shock?

One possibility is that there is a causal relationship between homeowners' race and purchase/sale prices. This is highlighted by Bayer et al. (2017), who find that Black and Hispanic homebuyers pay a premium of 2% on home purchases, possibly due to higher search costs for non-White buyers. If monetary tightening leads to a disproportionate increase in search costs for Black and Hispanic buyers, ultimately causing them to accept higher prices, it may explain why these groups experience lower home price appreciation relative to White buyers.

Another possibility is that this disparity stems not only from the direct effect of homeowners' race on transaction prices but also from residential segregation by race. Zonta (2019) reports that between 2013 and 2017, minority made up 51% of the population in neighborhoods where Black households typically purchase homes, compared to just 22% in neighborhoods where White households usually buy. Because Black and Hispanic homeowners often live in minority neighborhoods that rely on housing demand from Black and Hispanic households, a demand that is more sensitive to monetary policy shocks, their home price appreciation may be more significantly affected by changes in monetary policy than White households'.

This subsection explores the role of residential segregation by race in shaping racial disparities in home price appreciation following a monetary shock. We start by categorizing neighborhoods based on their White population share within their respective cities. Ideally, we would create many segments, allowing us to explore the heterogeneous impact of monetary policy on housing markets according to neighborhood characteristics. However, to accurately calculate HPIs, we need a sufficient number of transactions for each racial group within each neighborhood segment for every city in our sample. This necessarily limits the granularity of our analysis. In the end, we calculate the White population share at the census block level and group these blocks into three categories: low (bottom 20%), middle, and high (top 30%) concentrations of White residents. We will refer to these neighborhoods as minority, mixed and predominantly White neighborhoods. Following this classification, we construct home purchases, sales, and HPIs based on homeowners' race and the types of neighborhoods they occupy, resulting in a total of nine racial-by-neighborhood groups.

Using these newly constructed data, we investigate a dynamic system denoted by $[i_t, Y_{l,t}]$, where i_t represents the average federal funds rate in quarter t, and $Y_{l,t}$ is a vector consisting of net purchase intensity, home price appreciation, employment growth, and log of average earnings. Net purchase intensity and home price appreciation are observed for the nine groups, while employment growth and log of average earnings are observed for our three racial groups. To capture a broad range of temporal variation, we require that each city appear in at least ten quarters. Similarly, to capture a broad range of spatial variation for each period, we ensure that each quarter includes data from at least ten cities. In this exercise, our sample is reduced to 48 cities. This reduction is due to the challenge of constructing HPIs for all nine groups in some cities, given the insufficient numbers of complete ownership spells for certain race-by-neighborhood groups. We control for two lags of i_t and two lags of each variable in $Y_{l,t}$.

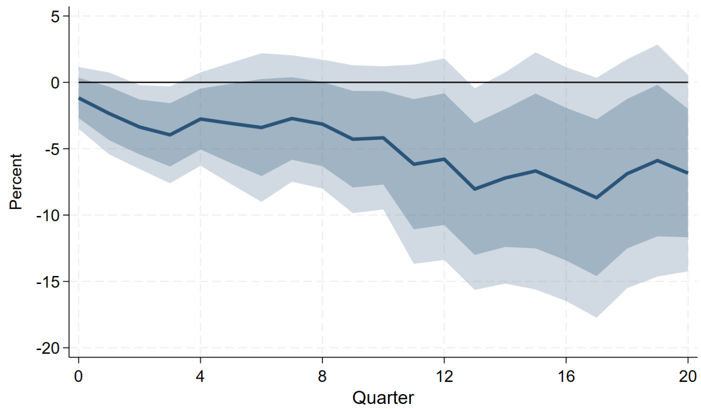
We replicate the analysis outlined in section 3.3 for these nine groups, focusing on the contrast between minority and predominantly White neighborhoods. Figure 10a plots the differences in cumulative changes in home price for White households living in minority versus predominantly White neighborhoods. Our results indicate that White households in minority neighborhoods experience a 7.7 percentage point steeper decline in home prices over sixteen quarters, following a 25-basis-point increase in the federal funds rate. Figure 10b presents similar results for Black households, showing an 11.1 percentage point steeper decline in home prices over sixteen quarters for those in minority neighborhoods. For Hispanic households, as shown in Figure 10c, those in minority neighborhoods experience a 7.2 percentage point steeper decline in home prices over the same period.

We also compare cumulative changes in home price for each racial group in mixed neighborhoods versus predominantly White neighborhoods. As shown in Appendix Figure E.2, although the point estimates are almost all negative, none of the differences are statistically significant. We extend the analysis to net purchase intensity, comparing mixed and minority neighborhoods against predominantly White neighborhoods. Appendix Figures E.3 and E.4 indicate that most estimates are not significantly different from zero.

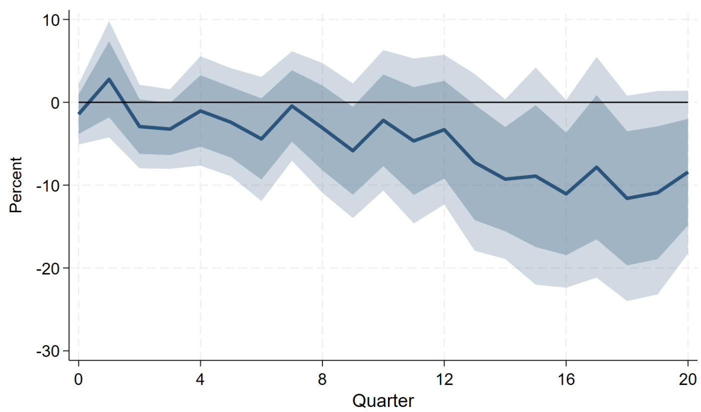
In summary, our findings indicate that while neighborhood racial composition has minimal impact on the response of net purchase intensity to monetary policy, it plays a significant role in how home prices react to monetary policy, beyond the influence of individual homeowner race. Intuitively, even if a contractionary monetary shock decreases housing demand from Black and Hispanic households relative to White households uniformly across neighborhoods, home prices in neighborhoods with higher reliance on non-White demand are more profoundly affected than

Figure 10: Responses of House Price for White, Black, and Hispanic Households: Minority Neighborhoods Versus Predominantly White Neighborhoods

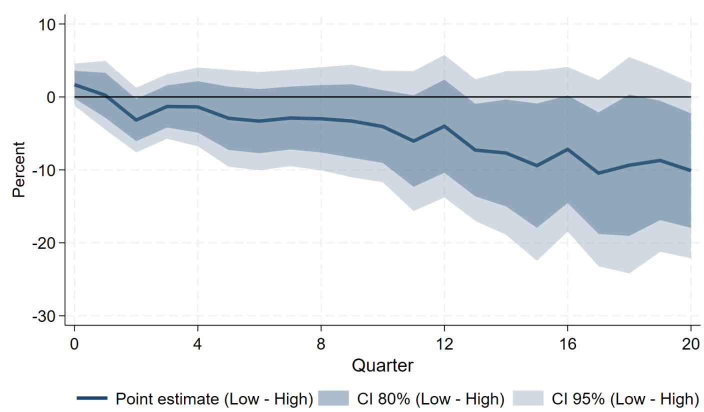
(a) White households



(b) Black households



(c) Hispanic households



Notes: Panels (a), (b), and (c) show the differences in impulse responses of cumulative (log) home price changes to a 25-basis-point increase in the federal funds rate for White, Black, and Hispanic households, respectively. Each panel compares the impulse responses between neighborhoods with low- and high-White population shares. Standard errors are clustered at the city level. The shaded areas represent the 80 percent and 95 percent confidence intervals.

those with lower dependence.

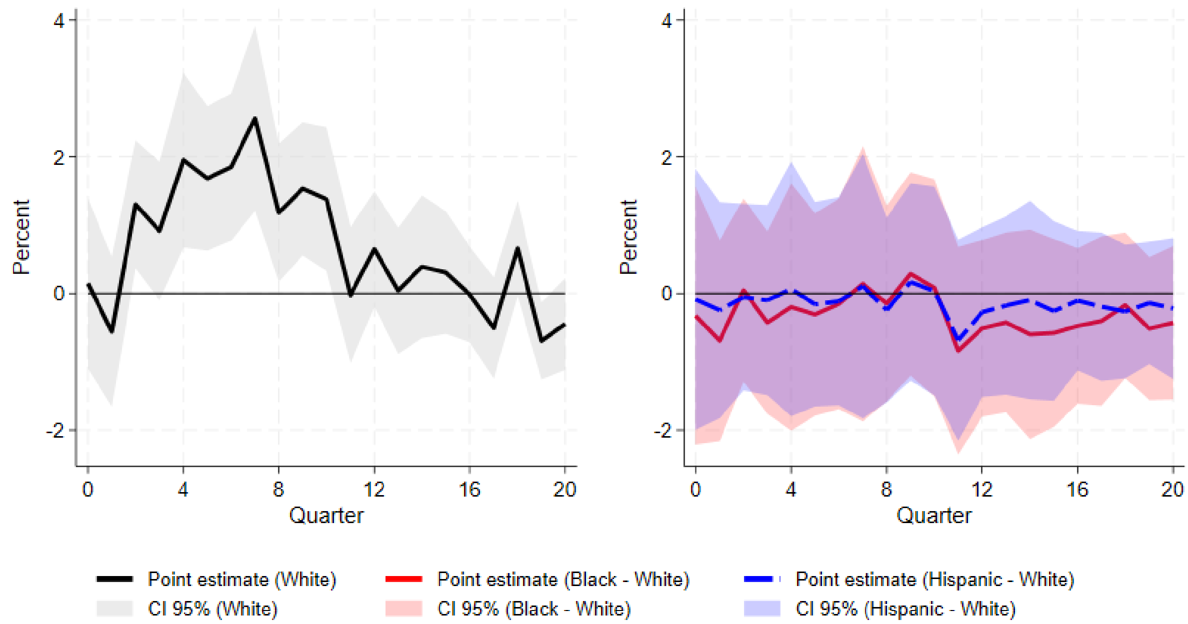
These findings have significant policy implications, suggesting that reducing residential segregation by race may lead to more uniform changes in housing demand across neighborhoods, thereby reducing disparities in home price appreciation, while also helping stabilize home values for minority households during monetary tightening.

4.2 Cash versus mortgage purchases

Since we rely on HMDA to identify the race of homeowners, we cannot observe the race of cash buyers, and our measures of home purchases and sales necessarily miss all cash transactions. Home purchases made with cash versus mortgage financing are a margin of substitution that may be affected by monetary policy. Could the observed relative reduction in home purchases by Black and Hispanic households be a result of these groups being more likely than White households to substitute mortgage purchases with cash purchases? To explore this possibility, we approximate the race-specific mortgage purchase share by calculating the ratio of ZIP code-based race-specific mortgage purchases to total purchases (including both cash and mortgage). It is important to acknowledge that this approximation method inherits the inaccuracies of the ZIP code-based approach used to construct race-specific purchases. However, it remains the best possible approximation, given the lack of data on the race of cash buyers.

The left panel of Figure 11 plots the impulse response of the mortgage purchase share to monetary policy for White households, while the right panel displays the differences between Black and White, and between Hispanic and White households. Monetary policy significantly affects the share of mortgage purchases for White households, increasing it by about 2 percent after four quarters, though this effect is not significant at sixteen quarters. However, there is no significant racial heterogeneity in these substitution patterns.

Figure 11: Response of Mortgage Purchase Share to Monetary Policy by Race



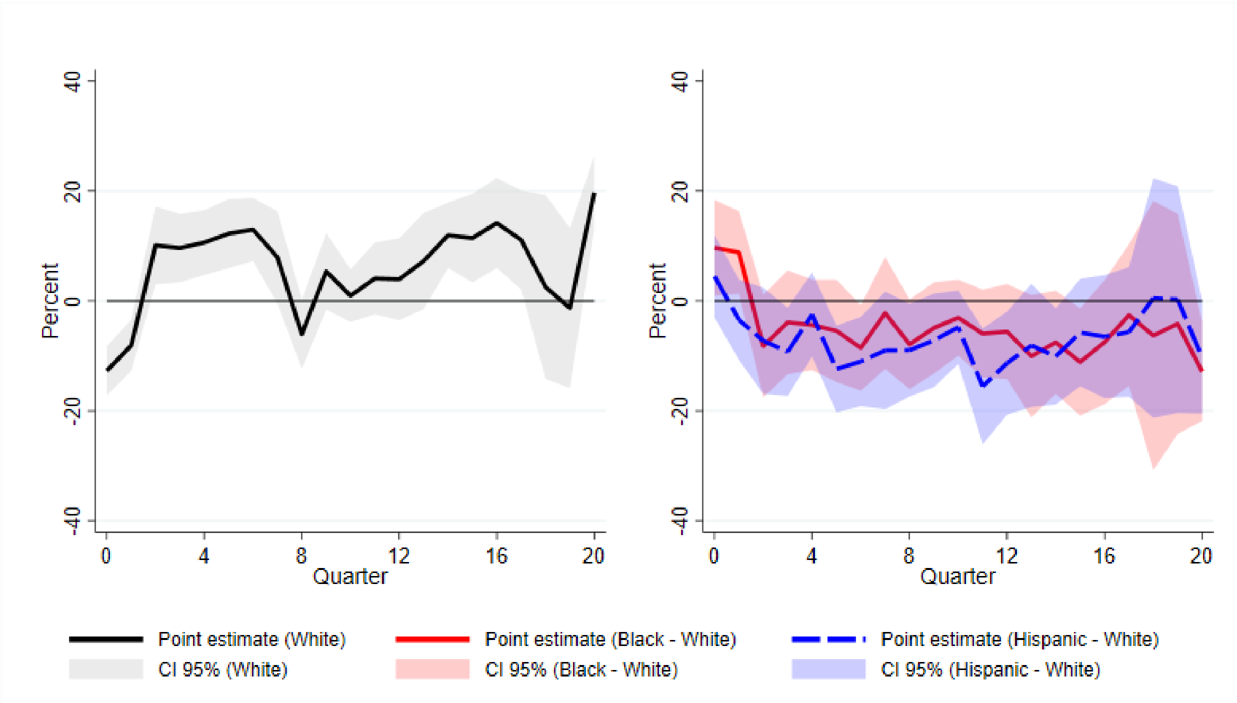
Notes: The figure presents the response of mortgage purchase share to a 25-basis-point increase in the federal funds rate. The impulse response of the White households is displayed on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

4.3 Home purchases with FHA loans

In section 3.2, we studied the effect of monetary policy on home purchases for different racial groups. A limitation of this analysis is that our measure of home purchases includes new entries into homeownership, upgrades, and purchases of second homes. Ideally, we would like to separately measure entries into homeownership, but this requires tracking individual market participants across properties and time. Due to the limited individual-level information in the CoreLogic–HMDA dataset and the extended period from 1995 to 2017, this is challenging to achieve with high confidence. One way to circumvent this issue is to look at home purchases made with FHA loans (FHA purchases, for short), on which CoreLogic and HMDA do provide information. According to Lee and Tracy (2023), from 2000 to 2022, around 83 percent of FHA purchase mortgages were issued to first-time buyers. Thus, FHA purchases are a good proxy for entry into homeownership.

The left panel of Figure 12 illustrates the impulse response of (log) FHA purchases to monetary policy for White households. The right panel of Figure 12 displays the differences in the impulse response of (log) FHA purchases to monetary policy between Black and White households and between Hispanic and White households. After two quarters, Black and Hispanic households experience a reduction in FHA purchases of 7.2 and 8.2 percentage points, respectively, compared to White households. This trend persists, with further declines of 7.9 and 9 percentage points for Black and Hispanic households, respectively, seen after two years. Since home purchases with FHA loans are indicative of entry into homeownership, this evidence suggests that monetary tightening has disproportionate adverse effects on Black and Hispanic homeownership.

Figure 12: Response of Purchase to Monetary Policy by Race, FHA Only



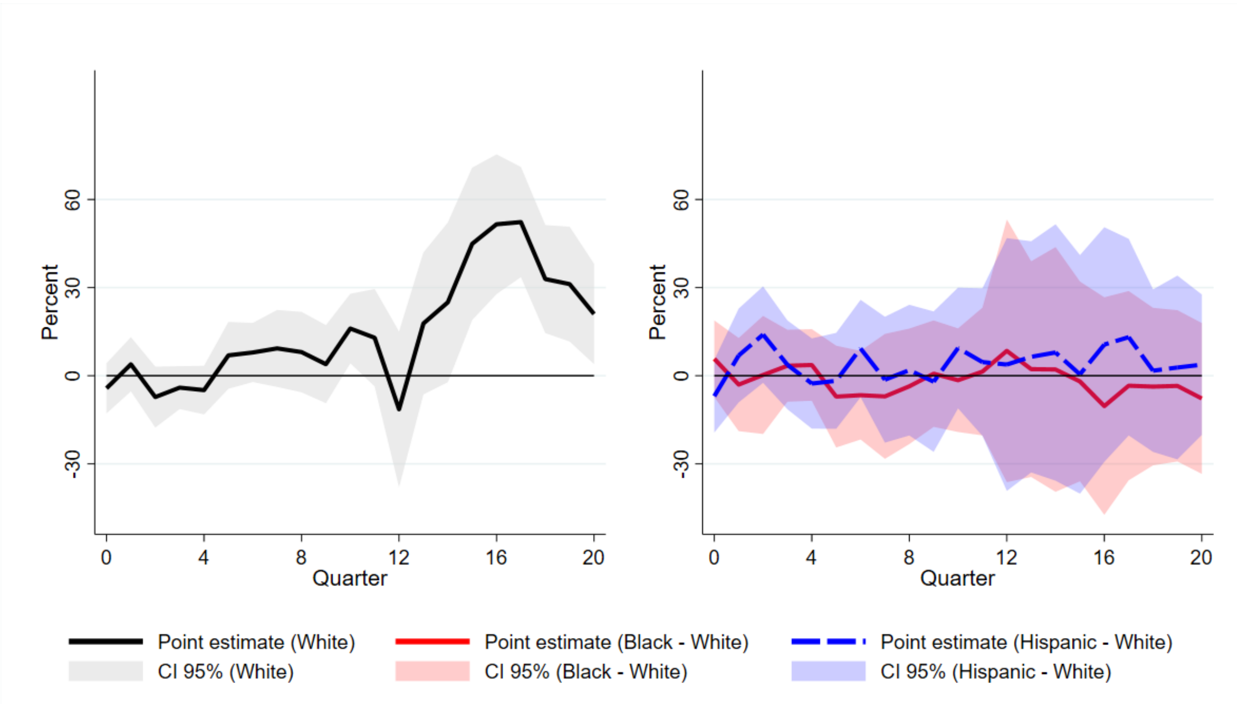
Notes: The figure presents the response of (log) FHA purchases to a 25-basis-point increase in the federal funds rate. The impulse response of the White households is displayed on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

4.4 Foreclosure and foreclosure-free HPIs

In section 3.2, we examined the impact of monetary policy on home sales across different racial groups. In this subsection, we focus on foreclosures for two reasons. First, foreclosures, as an important category of distressed sales, may exhibit behavior markedly different from non-distressed sales. Second, the data we use allow us to construct sufficiently long time series for the number of foreclosures and foreclosure-free HPIs at the city-quarter-race level. This is not possible for other types of distressed sales, such as short sales, as CoreLogic provides data on short sales only for transactions that occurred after 2006.

The left panel of Figure 13 plots the impulse response of (log of) the number of foreclosures to monetary policy for White households. The right panel of Figure 13 plots the differences in the impulse response between Black and White households, and between Hispanic and White households. Although foreclosures among White borrowers increase after 10 quarters, our analysis shows no statistically significant differences in the response of foreclosure to monetary policy between Black and White households or between Hispanic and White households.

Figure 13: Response of Foreclosure to Monetary Policy by Race

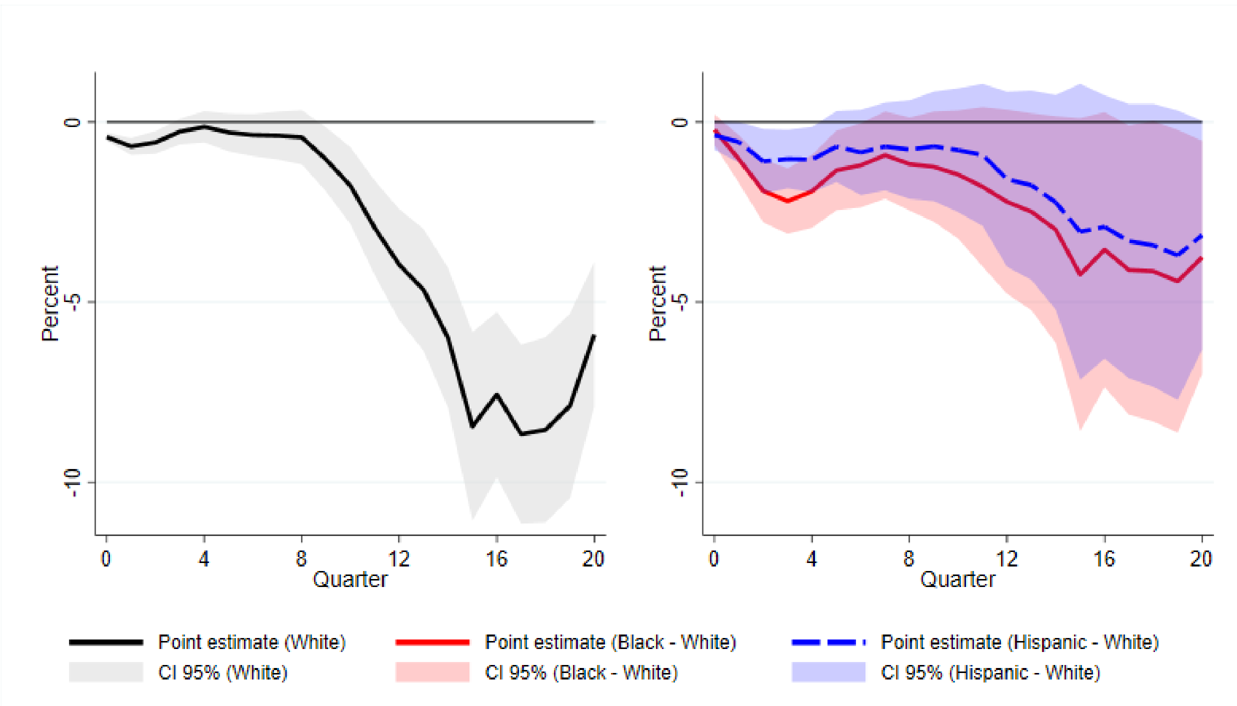


Notes: The figure presents the response of (log of) the number of foreclosures to a 25-basis-point increase in the federal funds rate. The impulse response of the White households is displayed on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

In section 3.3, we have studied the effect of monetary policy on race-specific HPIs estimated using microdata samples that include ownership spells ending in foreclosures. Thus, our baseline results take into account the effect of monetary policy on home prices through foreclosures and the associated price discounts. In this subsection, we also consider the effect of monetary policy on home prices that are not mediated through foreclosure. In Figure 14, we redo our baseline analysis using HPIs constructed by excluding foreclosures. The point estimates of the racial gaps, calculated as the differences in impulse responses between the Black and White series and between the Hispanic and White series, are quantitatively similar to the racial gaps that include foreclosures, as shown in the right panel of Figure 4b.

In conclusion, while racial disparities in foreclosures can play a significant role in driving racial disparities in realized housing returns (Kermani and Wong, 2021), our results indicate that racial gaps in home price appreciation following monetary tightening are not primarily driven by a relative increase in foreclosures among Black and Hispanic households. Therefore, foreclosure does not emerge in our analysis as a crucial channel through which monetary policy influences racial disparities in home price appreciation.

Figure 14: Response of Home Prices to Monetary Policy by Race, Excluding Foreclosures



Notes: The figure presents the response of (log) home price excluding foreclosures to a 25-basis-point increase in the federal funds rate. The impulse response of the White households is displayed on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

4.5 Effects of income

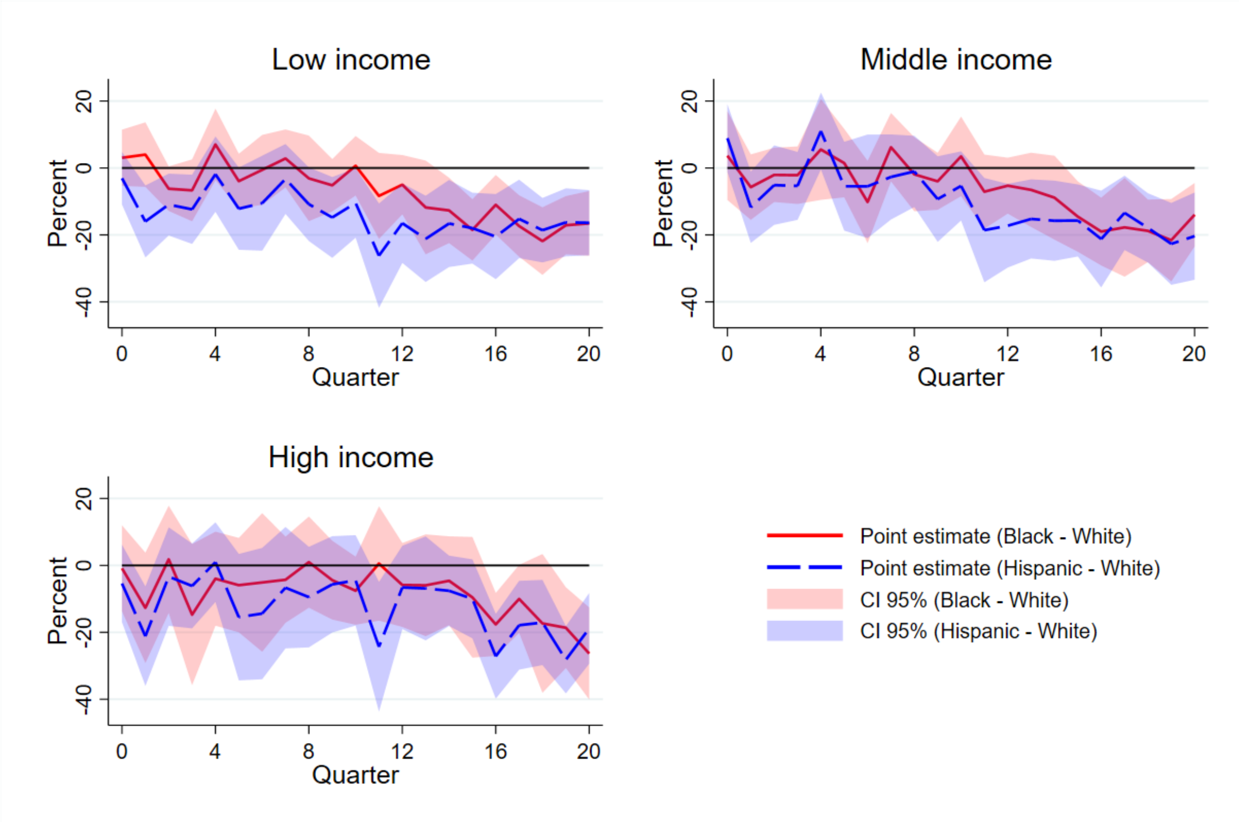
Some may argue that perceived racial disparity in responses to monetary policy is primarily the result of income gaps among racial groups. In 3.4, we have already examined whether the average earnings of different racial groups respond differently to monetary policy and found no significant racial differences in response. In this section, we further address this concern by examining differences in the impact of monetary policy by race within a particular income bracket.

We begin by categorizing the homeowners in our sample into three permanent income groups: low, middle, and high. This classification is based on the quantiles of mortgage applicant income for each city and quarter. Next, we construct home purchases, sales, and HPIs for each of the nine race and income groups. Using these newly constructed data, we investigate a dynamic system denoted by $[i_t, Y_{l,t}]$, where i_t represents the average federal funds rate in quarter t, and $Y_{l,t}$ is a vector consisting of net purchase intensity, home price appreciation, employment growth, and log of average earnings. Net purchase intensity and home price appreciation are observed for each of the nine groups, while employment growth and log of average earnings are observed for our three racial groups. In this exercise, our sample is reduced to 64 cities. This reduction is due to the inability to construct HPIs for all nine groups in some cities, where the number of observations is insufficient for certain race-by-income groups. We control for two lags of i_t and two lags of each variable in $Y_{l,t}$. We then repeat the analysis in section 3 for these nine groups.

In Figure 15, we present the response of net purchase intensity to monetary policy shocks. The three subfigures plot the responses of Black and of Hispanic households relative to White households within the same income group. Following a 25-basis-point increase in the federal funds rate, significant racial heterogeneity is observed in net purchase intensity for a given income group, particularly after sixteen quarters. Among low-income households, Black and Hispanic households experience decreases in net purchase intensity of 11 and 20.5 percentage points more, respectively, than their White counterparts over sixteen quarters. Similarly, among high-income households, the net purchase intensities of Black and Hispanic households decline by 17.6 and 27.1 percentage points more, respectively, compared to White households in the same time frame.

In summary, our analysis suggests that the effects of monetary policy on net home purchases display notable racial heterogeneity, even within a specific income group. Therefore, we believe that factors beyond permanent income play a role in shaping the divergent impact of monetary policy on housing outcomes across racial groups. As discussed previously, one such factor may be the racial differences in how employment responds to monetary policy.

Figure 15: Response of Net Purchase Intensity by Race and Income



Notes: The figure illustrates the differences in impulse responses of net purchase intensity between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) following a 25-basis-point increase in the federal funds rate. The subfigures represent the responses for low-income, middle-income, and high-income groups, respectively. Within each subfigure, White households are the baseline group. Standard errors are clustered at the city level, and the 95 percent confidence intervals are depicted by the shaded area.

4.6 Asymmetric effects of monetary policy

In this section, we explore the possibility of asymmetric effects arising from contractionary versus expansionary monetary policy. To do this, we separate the monetary surprise series into its positive and negative components and reformulate the reduced-form specification (2) into the following regression specification:

$$y_{l,t+h} = \beta_y^{\text{pos},(h)} \max(\text{MP}_t, 0) + \beta_y^{\text{neg},(h)} \min(\text{MP}_t, 0) + \text{controls} + \text{error}_{l,y,t}^{(h)}, \quad h = 0, 1, 2, \ldots \tag{3}$$

Here $\beta_y^{\text{pos},(h)}$ quantifies the h-quarter impact of a 100-basis-point increase in positive monetary surprise (contractionary shock). Similarly, $-\beta_y^{\text{neg},(h)}$ measures the h-quarter impact of a 100-basis-point increase in the absolute value of negative monetary surprise (expansionary shock). By decoupling the effects of positive and negative surprises, we can evaluate the impact of each component and assess which component is primarily responsible for the observed racial disparities in response or if both contribute equally.

Figure 16a displays the responses of the net purchase intensity to both positive/contractionary (left panel) and negative/expansionary monetary policy shocks (right panel). Each panel contrasts the impulse responses of Black and White households (solid red line) and of Hispanic and White households (dashed blue line). The left panel represents the difference of $0.25 \times (\beta^{pos,(h)}_{\text{net purchase,black}} - \beta^{pos,(h)}_{\text{net purchase,white}})$ and $0.25 \times (\beta^{pos,(h)}_{\text{net purchase,hispanic}} - \beta^{pos,(h)}_{\text{net purchase,white}})$; while the right panel represents $-0.25 \times (\beta^{neg,(h)}_{\text{net purchase,black}} - \beta^{neg,(h)}_{\text{net purchase,white}})$ and $-0.25 \times (\beta^{neg,(h)}_{\text{net purchase,hispanic}} - \beta^{neg,(h)}_{\text{net purchase,white}})$. In response to contractionary monetary policy surprises, Black and Hispanic households experience greater drops in net purchases than White households. In contrast, the differences among the three racial groups are relatively small in the case of an expansionary monetary policy surprise.

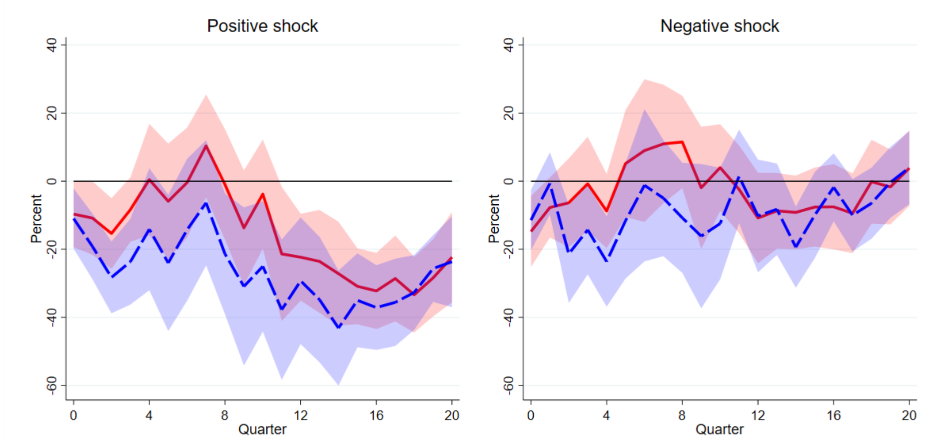
Similarly, Figure 16b displays the responses of cumulative home price appreciation to positive/contractionary (left panel) and negative/expansionary monetary policy shocks (right panel). In response to contractionary monetary shocks, both Black and Hispanic households see larger decreases in home price appreciation than White households, indicating a stronger adverse impact on minority groups. In contrast, home price appreciation responds similarly across all three racial groups in response to expansionary monetary shocks, indicating that the effects of negative monetary surprises do not differ significantly across racial groups.

The response of employment to monetary policy shocks is shown in Figure 16c. Black and Hispanic workers experience relatively worse responses to both positive and negative monetary surprises. In terms of point estimates, the adverse employment responses of Black and Hispanic workers are quantitatively larger during monetary tightening than during monetary easing.

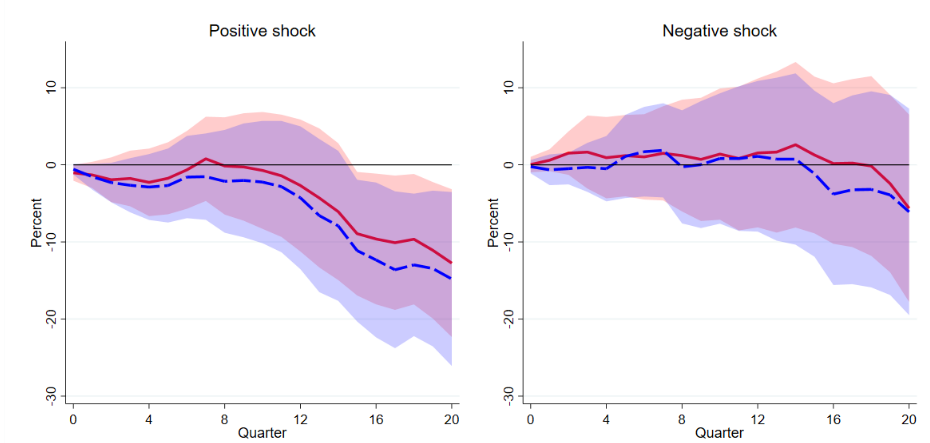
Overall, our analyses suggest that compared to White households, the net home purchases, home prices, and employment of Black and Hispanic households are more adversely affected by contractionary monetary policy and are equally or less advantageously affected by expansionary monetary policy. This highlights the asymmetric effects of monetary policy on racial inequalities in housing and labor markets: while monetary easing does not specifically benefit minorities, monetary tightening disproportionately hurts them compared to White households.

Figure 16: Responses to Positive and Negative Monetary Policy by Race

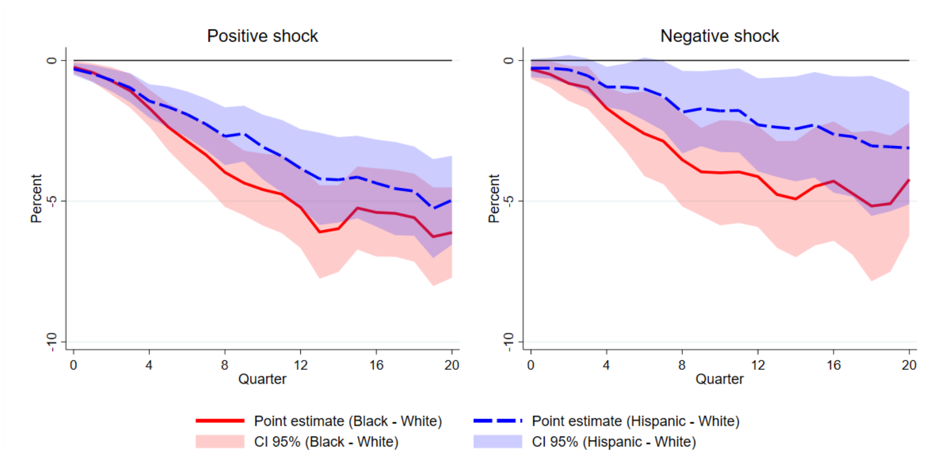
(a) Net purchase intensity



(b) Home price



(c) Employment



Notes: Panels (a), (b), and (c) display the responses of net purchase intensity, cumulative (log) home price change, and cumulative employment growth, respectively, to a monetary policy surprise. Each panel contrasts the impulse responses of Black and White households (solid red line) and of Hispanic and White households (dashed blue line). The left side of each panel depicts the impulse responses to a positive/contractionary surprise, while the right side shows the impulse responses to a negative/expansionary surprise. Standard errors are clustered at the city level, with 95 percent confidence intervals represented by the shaded areas.

5 Conclusion

In the past decade, awareness has grown among central bankers, politicians, and activists regarding the distributional effects of monetary policy. Our study offers new insights into the relationship between monetary policy and racial disparities in home purchases, sales, and home price appreciation. Our estimates show that Black and Hispanic households exhibit heightened sensitivity in their responses to monetary policy shocks compared to White households. We also find that the racial differences in the response of home prices to monetary policy can be attributed to residential segregation by race. Although our research focuses on the housing sector, the implications of these findings may extend beyond housing. Studies such as Iacoviello and Neri (2010) have shown that spillover effects from the housing market to consumption are non-negligible and become increasingly relevant over time. Therefore, addressing racial disparities in housing outcomes may have broader implications for overall racial inequality in consumption.

Our study highlights how contractionary monetary policy can unintentionally worsen racial inequality in the housing market. The findings suggest that efforts to reduce residential segregation by race may result in more uniform changes in housing demand across neighborhoods during monetary policy cycles, thereby helping to mitigate racial disparities in home price depreciation following monetary tightening. Policymakers can use this information to develop policies that reduce disparities, ensuring more equitable outcomes.

Furthermore, our analysis underscores the importance of the employment channel in explaining the excess responsiveness of Black and Hispanic housing outcomes to monetary tightening. The more substantial impact of monetary policy on Black and Hispanic employment compared to White employment is an important factor contributing to the observed excess responsiveness. Although we highlight the employment channel in this study, it is essential to recognize that there may be other channels at work. It could be fruitful for future research to explore how monetary policy interacts with racial differences in financial literacy, the mortgage approval rate, the propensity to prepay or refinance mortgages, the take-up of adjustable rate mortgages, and non-interest financing costs.

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Appendix for Online Publication

Appendix A Details of the HMDA Data and the CoreLogic–HMDA Merging Procedure

In this section, we provide details of the HMDA data and the CoreLogic–HMDA merging procedure. The HMDA data capture the near-universe of mortgage originations. The data are available on an annual frequency. Each loan application has several key pieces of information: the year of the application, the lender's decision, the securitization status of the loan, the gender of the applicant, the race and ethnicity of each applicant (and co-applicant, if any), loan amount, income, state, county, and census tract where the home is located. The data also provide useful information on the lender, such as the name of the institution, its type, and its regulating agency.[26] HMDA data became available in the early 1990s.

For our study, it is crucial to maintain consistent coding of race and ethnicity variables for both the applicant and co-applicant throughout the entire sample period. Before 2004, the HMDA only permitted an applicant to report one race: "American Indian or Alaska Native", "Asian or Pacific Islander", "Black", "Hispanic", "White", or "Other". This rule also applied to any co-applicant. In 2004, following changes in the 2000 US Census, HMDA revised how it recorded race and ethnicity. Instead of considering Hispanic descent as a race, HMDA began recording race and Hispanic ethnicity separately, allowing individuals of any race to identify as Hispanic. Additionally, both applicants and co-applicants could now report up to five races.

To ensure uniformity of the race and ethnicity variables across the entire sample period, we recode the post-2004 race/ethnicity variables to be consistent with their coding prior to 2004. We apply the following coding methodology. An applicant (and any potential co-applicant) reporting Hispanic ancestry prior to 2004 is assigned to the Hispanic category. An applicant who reports being Black or White prior to 2004 is recorded as non-Hispanic Black and non-Hispanic White, respectively. Starting from 2004, an applicant (and any potential co-applicant) reporting they are White in the race category and non-Hispanic in the ethnicity category is categorized as non-Hispanic White. Likewise, an applicant (and any potential co-applicant) reporting they are Black and non-Hispanic is categorized as non-Hispanic Black. From the 2004 HMDA onward, both primary and any potential co-applicants can denote multiple racial identities. In our data, households labeled as White or Black are those that have reported only one racial identity, whereas those in our Hispanic segment may have reported multiple racial identities. Homeowners who are not categorized as non-Hispanic Black, non-Hispanic White, or Hispanic may be, for example,

[26] The HMDA data have two fields "respondent_id", and "agency_code" to identify a lender. These variables can be linked to the lender's information using the crosswalk dataset constructed by Robert Avery. The crosswalk dataset is obtained at Neil Bhutta's website https://sites.google.com/site/neilbhutta/data.

mixed-race homeowners, individuals with multiple racial identifications, non-Hispanic Asians, or non-Hispanic Pacific Islanders. Also included are scenarios in which only the primary or co-applicant identifies as Hispanic, while the other does not.

In order to align the CoreLogic and HMDA datasets, it is crucial to reconcile the differences in their address specifications. CoreLogic assigns each property to a 2010 census block number, while HDMA limits address information to the census tract number. This census tract number in the HMDA data evolves with the decennial census updates: 1993–2002 data are mapped to the 1990 census tract, 2003–2011 align with the 2000 tract, and 2012–2017 reflect the 2010 tract. To bridge these variances, we lean on the census block relationship files from the official US Census website.[27] This strategy allows us to link the evolving HMDA census tract numbers to the 2010 census block numbers.

For each mortgage transaction in the CoreLogic dataset, we search for possible matching mortgage applications in the HMDA data based on the exact origination year, census tract, loan type, and loan amount. We then fine-tune these matches by comparing the textual similarity of lender names, keeping only those that are of high similarity. We conduct an analysis of the matching rate along three dimensions: house transaction price, neighborhood White population share, and neighborhood median income. The results are presented in Table A.1. In panel (a), we examine the matching rate between CoreLogic and HMDA data based on the house transaction price. Housing transactions in CoreLogic are divided into three groups based on transaction price within each city-quarter, and we calculate the proportion of transactions within each group that are matched to HMDA data. The analysis shows that there are no substantial differences in the matching rate among the three groups. Similarly, in panel (b), we investigate the matching rate based on the neighborhood-level White population share within a city. Housing transactions in CoreLogic are divided into three groups based on the White population share of the census block group where the house is located within a city. Again, we find no significant differences in the matching rate among the three groups. Finally, in panel (c), we assess the matching rate based on the neighborhood-level median household income within a city. Housing transactions in CoreLogic are divided into three groups based on the median household income of the census block group where the house is located within a city. The analysis demonstrates that there are no substantial differences in the matching rate between the three groups. Overall, these results indicate that our matching method does not generate significant selection bias along these dimensions.

[27] See https://www.census.gov/geographies/reference-files/2010/geo/relationship-files.html.

Appendix Table A.1: Matching Rate Analysis

(a) House Price	# of Transactions	# of Matches	Matching Rate
Low	20700732	10727003	0.52
Middle	20890648	11474231	0.55
High	20961178	11379198	0.54
(b) Neighborhood White Population Share	# of Transactions	# of Matches	Matching Rate
Low	20641040	10768551	0.52
Middle	20784490	11268578	0.54
High	21017432	11517090	0.55
(c) Neighborhood Median Income	# of Transactions	# of Matches	Matching Rate
Low	20681980	10873438	0.53
Middle	20720888	11156979	0.54
High	20484524	11229846	0.55

Notes: This table presents the matching rate between CoreLogic and the HMDA data along three dimensions. Panel (a) groups CoreLogic housing transactions by house price within each city-quarter. Panel (b) groups CoreLogic transactions by White population share at the census block group level within a city. Panel (c) groups CoreLogic transactions by median household income at the census block group level within a city. We then calculate the proportion of transactions within each group that are matched to the HMDA data. Non-Hispanic White population share and median household income data come from the five-year summary file of the 2017 American Community Survey.

Table A.2 summarizes the matched data. Among the nearly 13 million complete ownership spells, the median purchase year is 2005, and the median sale year is 2012. The sales price on average is \$305,000, with the median price being \$230,000. In terms of homeowner demographics, roughly 65% identify as White, 5.4% as Black, and 9.7% as Hispanic; the remaining 20% fall into other racial and ethnic classifications. The median loan-to-value (LTV) ratio is 80%, and the majority (60%) of the loans are conventional 30-year mortgages. We have data on 3.4 million mortgage rates, of which the average and median are 6.1 percentage points.

Appendix Table A.2: Summary Statistics of Matched CoreLogic–HMDA Data of Complete Ownership Spells

	count	mean	sd	p10	p50	p90
Purchase Year	12,821,389	2005.4	5.7	1998	2005	2014
Sale Year	12,821,389	2011.6	6.0	2003	2012	2019
Purchase Price (Thousands)	12,821,389	264.3	2922.1	90.0	199.3	486.5
Sale Price (Thousands)	12,821,389	304.7	4107.7	88.6	230.0	560.0
Ownership Spell (Years)	12,821,389	6.2	4.4	1.7	5.0	12.5
Annualized Price Appreciation (%)	12,564,963	2.4	11.8	-9.8	2.7	13.9
White	12,821,389	0.649	0.5	0.0	1.0	1.0
Black	12,821,389	0.054	0.2	0.0	0.0	0.0
Hispanic	12,821,389	0.097	0.3	0.0	0.0	0.0
Income (Thousands)	12,406,011	99.8	159.8	35.0	73.0	173.0
FHA	12,821,389	0.2	0.4	0.0	0.0	1.0
ARM	6,344,654	0.5	0.5	0.0	0.0	1.0
Loan-to-Value (%)	12,565,013	78.1	23.9	29.6	80.0	99.7
30-Year Conventional Loan (%)	12,821,389	0.6	0.5	0.0	1.0	1.0
Mortgage Rate (%)	3,436,696	6.1	1.6	4.1	6.1	8.1

Notes: Our sample consists of completed ownership spells (i.e., the purchase and sale of a given house). All purchases were made between 1993 and 2017 and all sales were completed by the end of 2021. Purchase and Sale Years represent the years in which the purchase and sale transactions occurred for a given ownership spell. Purchase and Sale Prices indicate the transaction prices associated with the purchase and the sale, respectively. Ownership Spell measures the length of time between the purchase and sale dates. Annualized Price Appreciation represents the annualized rate of appreciation. White/Black/Hispanic are binary indicators denoting the respective racial groups. Income represents the total gross annual income used by the lender to make the credit decision. FHA and ARM are binary indicators of FHA-insured and adjustable-rate mortgages, respectively. Loan-to-Value represents the ratio of the mortgage amount at the time of origination to the purchase price. The binary indicator of 30-year Conventional Loan indicates 30-year mortgages that are not backed by a government agency. Mortgage Rate refers to the interest rate associated with the 30-year Conventional Loan.

Appendix B List of Cities

Table B.1 provides a list of the 136 cities analyzed in this study, which includes 110 Metropolitan Statistical Areas and 26 Metropolitan Divisions.[28] The codes and names listed in Table B.1 are consistent with the 2018 county-to-MSA crosswalk provided by the US Census Bureau, which is also utilized in recent FHFA HPI reports.[29] Figure B.1 plots the geographical distribution of the cities.

Appendix Table B.1: List of city codes and city names

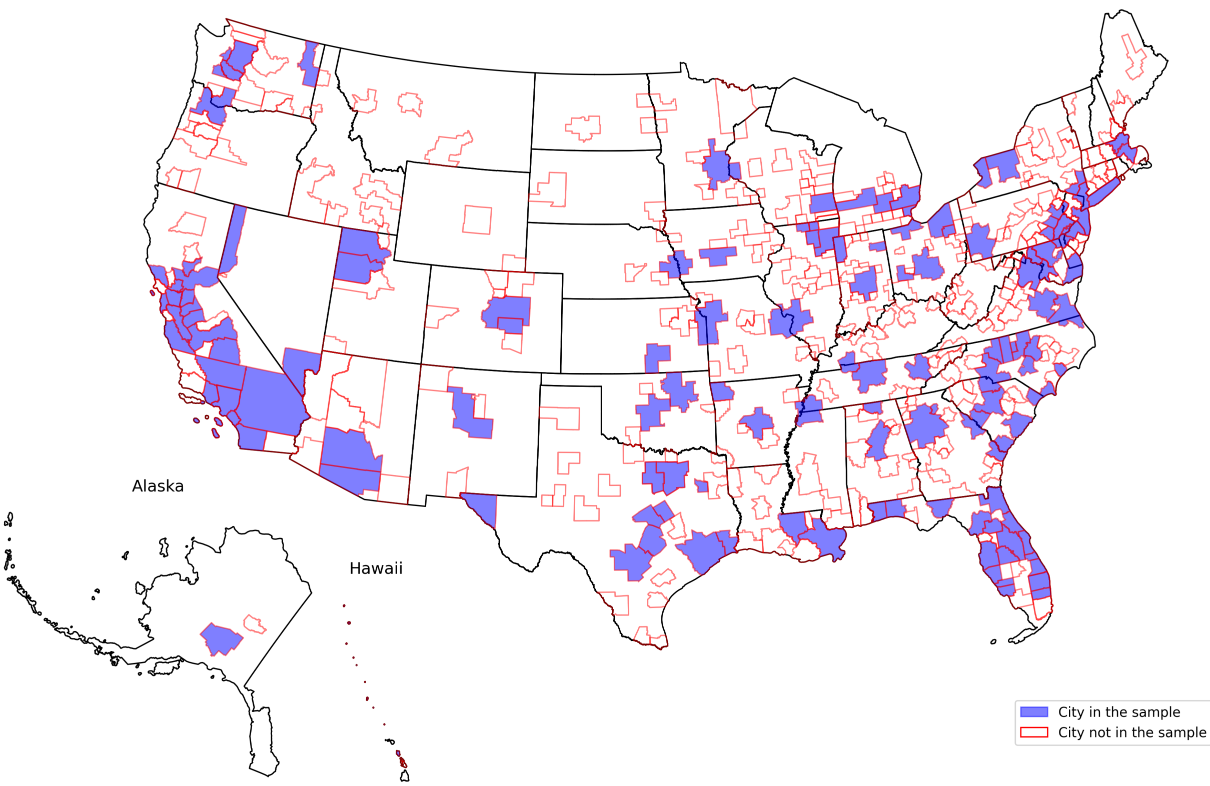
City Code	City Name	City Code	City Name
10420	Akron, OH	33460	Minneapolis-St. Paul-Bloomington, MN-WI
10740	Albuquerque, NM	33700	Modesto, CA
10900	Allentown-Bethlehem-Easton, PA-NJ	33874	Montgomery County-Bucks County-Chester County, PA
11244	Anaheim-Santa Ana-Irvine, CA	34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC
11260	Anchorage, AK	34980	Nashville-Davidson–Murfreesboro–Franklin, TN
12060	Atlanta-Sandy Springs-Alpharetta, GA	35004	Nassau County-Suffolk County, NY
12260	Augusta-Richmond County, GA-SC	35154	New Brunswick-Lakewood, NJ
12420	Austin-Round Rock-Georgetown, TX	35380	New Orleans-Metairie, LA
12540	Bakersfield, CA	35614	New York-Jersey City-White Plains, NY-NJ
12580	Baltimore-Columbia-Towson, MD	35840	North Port-Sarasota-Bradenton, FL
12940	Baton Rouge, LA	36084	Oakland-Berkeley-Livermore, CA
13140	Beaumont-Port Arthur, TX	36100	Ocala, FL
13820	Birmingham-Hoover, AL	36260	Ogden-Clearfield, UT
14454	Boston, MA	36420	Oklahoma City, OK
14740	Bremerton-Silverdale-Port Orchard, WA	36500	Olympia-Lacey-Tumwater, WA
15380	Buffalo-Cheektowaga, NY	36540	Omaha-Council Bluffs, NE-IA
15500	Burlington, NC	36740	Orlando-Kissimmee-Sanford, FL
15764	Cambridge-Newton-Framingham, MA	37100	Oxnard-Thousand Oaks-Ventura, CA
15804	Camden, NJ	37340	Palm Bay-Melbourne-Titusville, FL
15980	Cape Coral-Fort Myers, FL	37860	Pensacola-Ferry Pass-Brent, FL
16700	Charleston-North Charleston, SC	37964	Philadelphia, PA
16740	Charlotte-Concord-Gastonia, NC-SC	38060	Phoenix-Mesa-Chandler, AZ
16984	Chicago-Naperville-Evanston, IL	38300	Pittsburgh, PA
17300	Clarksville, TN-KY	38900	Portland-Vancouver-Hillsboro, OR-WA
17460	Cleveland-Elyria, OH	38940	Port St. Lucie, FL
17820	Colorado Springs, CO	39100	Poughkeepsie-Newburgh-Middletown, NY

[28]For context, the FHFA Purchase-Only Indexes, which are non-race specific and estimated using sales price data, are available for the 100 largest MSAs on their website https://www.fhfa.gov/data/hpi/datasets?tab=quarterly-data. Our final dataset covers 86 of these MSAs, with the reduction from 100 to 86 almost entirely due to our requirement that there be a sufficient number of transactions to construct race-specific HPIs for all three racial groups.

[29]The county-to-MSA crosswalk file, which includes columns for the CBSA Code, Metropolitan Division Code, CBSA Title, and Metropolitan Division Title, is available at https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/historical-delineation-files.html. In Table B.1, the 'City Code' column reflects the CBSA Code for MSAs and the Metropolitan Division Code for Metropolitan Divisions, while the 'City Name' column corresponds to the CBSA Title for MSAs and the Metropolitan Division Title for Metropolitan Divisions.

17900	Columbia, SC	39460	Punta Gorda, FL
18140	Columbus, OH	39580	Raleigh-Cary, NC
18880	Crestview-Fort Walton Beach-Destin, FL	39740	Reading, PA
19124	Dallas-Plano-Irving, TX	39900	Reno, NV
19430	Dayton-Kettering, OH	40060	Richmond, VA
19660	Deltona-Daytona Beach-Ormond Beach, FL	40140	Riverside-San Bernardino-Ontario, CA
19740	Denver-Aurora-Lakewood, CO	40380	Rochester, NY
19780	Des Moines-West Des Moines, IA	40420	Rockford, IL
19804	Detroit-Dearborn-Livonia, MI	40900	Sacramento-Roseville-Folsom, CA
20500	Durham-Chapel Hill, NC	41180	St. Louis, MO-IL
20994	Elgin, IL	41500	Salinas, CA
21340	El Paso, TX	41540	Salisbury, MD-DE
22180	Fayetteville, NC	41620	Salt Lake City, UT
22220	Fayetteville-Springdale-Rogers, AR	41700	San Antonio-New Braunfels, TX
22744	Fort Lauderdale-Pompano Beach-Sunrise, FL	41740	San Diego-Chula Vista-Carlsbad, CA
23060	Fort Wayne, IN	41884	San Francisco-San Mateo-Redwood City, CA
23104	Fort Worth-Arlington-Grapevine, TX	41940	San Jose-Sunnyvale-Santa Clara, CA
23224	Frederick-Gaithersburg-Rockville, MD	42220	Santa Rosa-Petaluma, CA
23420	Fresno, CA	42340	Savannah, GA
23540	Gainesville, FL	42644	Seattle-Bellevue-Kent, WA
23580	Gainesville, GA	42680	Sebastian-Vero Beach, FL
23844	Gary, IN	44060	Spokane-Spokane Valley, WA
24340	Grand Rapids-Kentwood, MI	44700	Stockton, CA
24660	Greensboro-High Point, NC	45104	Tacoma-Lakewood, WA
25940	Hilton Head Island-Bluffton, SC	45220	Tallahassee, FL
26420	Houston-The Woodlands-Sugar Land, TX	45300	Tampa-St. Petersburg-Clearwater, FL
26620	Huntsville, AL	45780	Toledo, OH
26900	Indianapolis-Carmel-Anderson, IN	46060	Tucson, AZ
27260	Jacksonville, FL	46140	Tulsa, OK
27340	Jacksonville, NC	46340	Tyler, TX
28140	Kansas City, MO-KS	46520	Urban Honolulu, HI
28660	Killeen-Temple, TX	46700	Vallejo, CA
28940	Knoxville, TN	47260	Virginia Beach-Norfolk-Newport News, VA-NC
29460	Lakeland-Winter Haven, FL	47300	Visalia, CA
29540	Lancaster, PA	47380	Waco, TX
29620	Lansing-East Lansing, MI	47664	Warren-Troy-Farmington Hills, MI
29820	Las Vegas-Henderson-Paradise, NV	47894	Washington-Arlington-Alexandria, DC-VA-MD-WV
30780	Little Rock-North Little Rock-Conway, AR	48424	West Palm Beach-Boca Raton-Boynton Beach, FL
31084	Los Angeles-Long Beach-Glendale, CA	48620	Wichita, KS
32820	Memphis, TN-MS-AR	48864	Wilmington, DE-MD-NJ
32900	Merced, CA	49180	Winston-Salem, NC
33340	Milwaukee-Waukesha, WI	49700	Yuba City, CA

Appendix Figure B.1: Geographic Distribution of US Cities with Constructed Housing Metrics



Appendix C Comparison of the Alternative Method with the CoreLogic–HMDA Match Method

Our method relies on merging CoreLogic data with HMDA data to accurately identify the race of homeowners. An alternative approach involves constructing race-specific housing market metrics, using non-race-specific datasets at the ZIP code level, combined with ZIP code-level racial composition data. In this section, we outline the process for constructing these alternative measures and compare them to our original metrics.

Alternative Method for Race-Specific Purchase and Sale Let z represent a ZIP code. For each city l, each quarter t, and each racial group r, we calculate the alternative measure of $\text{Purchase}_{l,t,r}$ as $\sum_{z \in l} \text{Purchase}_{z,t} \times \frac{\text{Population}_{z,t,r}}{\sum_r \text{Population}_{z,t,r}}$, where the summation is over all ZIP codes z within city l.

Although this approach does not require merging CoreLogic data with HMDA data, it assumes that within each ZIP code, a racial group's share of purchases and sales is directly proportional to its population share. To quantify the accuracy the alternative method loses by imposing such a strong assumption, we calculate city-quarter-level purchase share by race, $\frac{\text{Purchase}_{l,t,r}}{\sum_r \text{Purchase}_{l,t,r}}$, using both our original method and the alternative method.

In practice, we construct alternative measures of race-specific purchases and sales based on Census ZIP Code Tabulation Areas (ZCTAs) rather than ZIP codes, as racial composition data is only available at the ZCTA level. More than 80% of the ZCTAs correspond to a single ZIP code, although some ZCTAs encompass multiple ZIP codes. We obtain ZCTA population counts by race from the U.S. Census for the years 1990, 2000, and 2010.[30] For quarters between 1990 and 1999, we use 1990 census data; for quarters between 2000 and 2009, we use 2000 census data; and for quarters from 2010 onward, we use 2010 census data. To calculate ZCTA-level (non-race-specific) purchases and sales, we first count the purchases and sales in CoreLogic for each ZIP code, then aggregate them to the ZCTA level using a ZIP code-to-ZCTA crosswalk.[31] Since some ZIP codes are not covered in CoreLogic, we only include ZCTAs where all ZIP codes are covered. If a ZIP code matches multiple ZCTAs, we distribute purchases and sales evenly among the matched ZCTAs. We then merge the ZCTA-level data on home purchases/sales and racial composition with a ZCTA-to-county crosswalk, followed by a county-to-city crosswalk. If a ZCTA matches multiple cities, we divide purchases, sales, and population counts evenly among the matched cities. For each city, we calculate a city-level coverage ratio by dividing the number of ZCTAs with available home purchase/sale and racial composition data by the total number of ZCTAs that should be matched to that city. Only cities with a coverage ratio greater than 0.5 are retained.

[30] Data can be downloaded from IPUMS NHGIS https://www.nhgis.org/. The variable names for non-Hispanic White, non-Hispanic Black, and Hispanic population counts are cw7aaYYYY, cw7abYYYY, and cp4abYYYY, respectively, where YYYY corresponds to the years 1990, 2000, and 2010.

[31] The ZIP code-to-ZCTA crosswalk data is obtained from the U.S. Department of Housing and Urban Development website at https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

We then calculate alternative measures of race-specific purchases and sales and merge them with the measures constructed using our original method. The alternative measures are available for 77 percent of the city and quarter data used in our final regression sample. The mean purchase share for White households is 78.8 percent with the alternative method and 84.7 percent with our method. As shown in Figure 2, the alternative method significantly overestimates the purchases and sales made by Black and Hispanic households. The entire distribution of Black and Hispanic household purchases and sales is shifted to the right with the alternative method. Specifically, using the alternative method, the Black purchase share increases from 5.6 percent to 9.3 percent, and the Hispanic purchase share increases from 9.7 percent to 11.9 percent. The differences in the mean of the data constructed from the two methods for the same racial groups are statistically different from zero.

We also repeat the exercise mentioned above but restrict the aggregated data from both methods to only include cities and quarters where the matching rate between CoreLogic and HMDA is at least 70 percent. As shown in Appendix Figure C.1, the mean purchase share for White households is 82 percent with the alternative method and 90.4 percent with our method. The alternative method significantly overestimates the purchases and sales made by Black and Hispanic households. The entire distribution of Black and Hispanic household purchases and sales is shifted to the right with the alternative method. Specifically, using the alternative method, the Black purchase share increases from 3.5 percent to 7.5 percent, and the Hispanic purchase share increases from 6.1 percent to 10.4 percent. The differences in the mean of the data constructed from the two methods for the same racial groups are statistically different from zero.

The previous discussion focused on race-specific purchase shares, but we have not yet addressed sales. Rather than repeating the same method for sales, we took a different approach. Since the data comprise complete ownership spells, where every purchase corresponds to a sale, total purchases equal total sales at the city level. We calculated the transaction share by race at the city level, with total transactions as $\text{transactions}_l = \sum_t \text{purchases}_{l,t}$ and race-specific transactions as $\text{transactions}_{l,r} = \sum_t \text{purchases}_{l,r,t}$. Then $\text{transaction share}_{l,r}$ is $\text{transactions}_{l,r}/\text{transactions}_l$. As shown in Appendix Figure C.2, the alternative method significantly overestimates the transactions made by Black and Hispanic households.

Alternative Method for Race-Specific HPI Let z represent a ZIP code. For each city l, year t and race r, we calculate the alternative measures of $\text{HPI}_{l,t,r}$ as $\sum_{z\in l}(\text{HPI}_{z,t} \times \frac{\text{population}_{z,t,r}}{\sum_z \text{population}_{z,t,r}})$, where the summation is over all ZIP codes z within city l.

We obtain the annual five-digit ZIP code HPI from the FHFA.[32] We apply the same methodology as described earlier to match ZIP codes to ZCTAs, and subsequently to cities. However, FHFA HPI data does not provide full coverage for all ZIP codes within each city. To account for this, we

[32] See https://www.fhfa.gov/data/hpi/datasets?tab=additional-data.

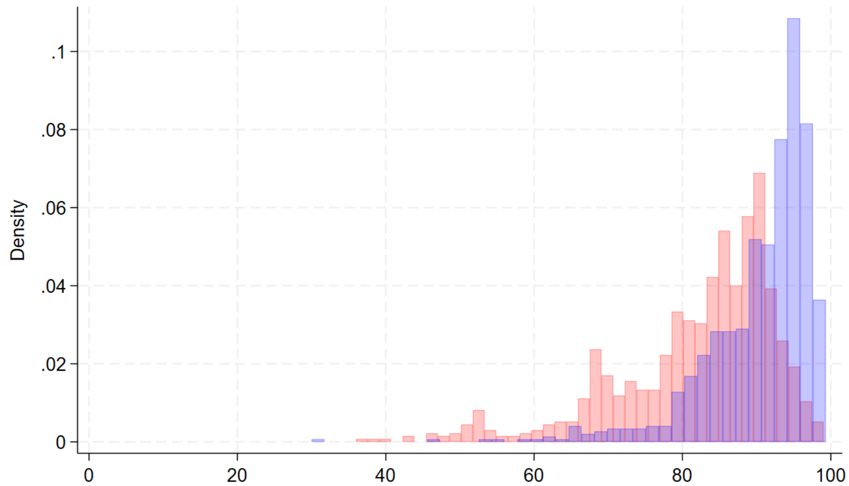
calculate a city-level coverage ratio by dividing the number of ZCTAs matched with FHFA data by the total number of ZCTAs associated with each city. Cities with a coverage ratio greater than 0.5 were retained for analysis.

To evaluate the potential inaccuracies of this alternative method, we merge the data constructed using this approach with our final regression sample. Due to the incomplete ZIP code coverage in the FHFA data, the merged dataset represents 45 percent of our final sample. We then calculate the annual change in log HPI. Since our CoreLogic–HMDA method calculates quarterly HPIs, we first calculate the Q4-to-Q4 change before comparing it with the alternative method, which is at an annual frequency. The results remain robust even when using the Q1-to-Q1 change.

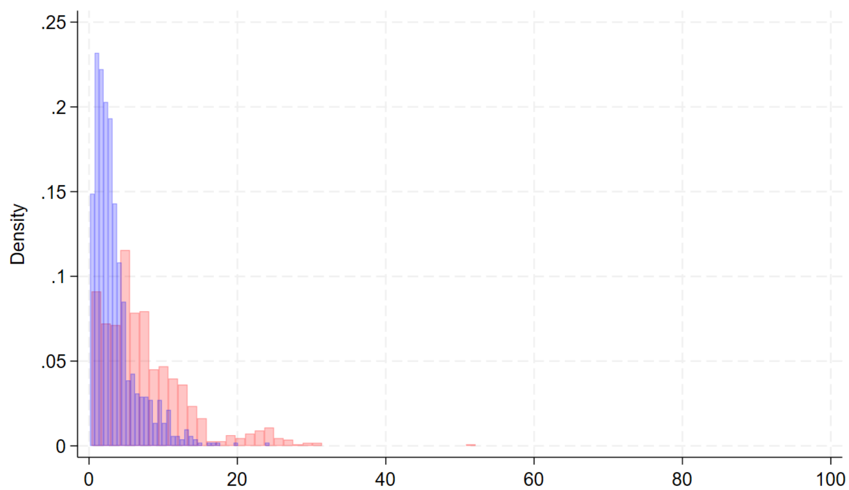
Appendix Figure C.3 shows the differences in the annual change in log HPI calculated using the two methods. Specifically, the mean of annual changes calculated using the alternative method is approximately 0.029 percent for all three racial groups, compared to 0.028, 0.014, and 0.017 percent, respectively, using the CoreLogic–HMDA method. The standard deviation of annual changes for White households increases from 0.08 percent using the alternative method to 0.15 percent using the CoreLogic–HMDA method. For Black households, it increases from 0.09 percent to 0.37 percent, and for Hispanic households, it increases from 0.09 percent to 0.29 percent, when comparing the alternative method to the CoreLogic–HMDA method.

Appendix Figure C.1: Comparison of the Alternative Method with the CoreLogic–HMDA Method: Purchase Share (Percent) Distribution for Matching Rate at Least 70 Percent

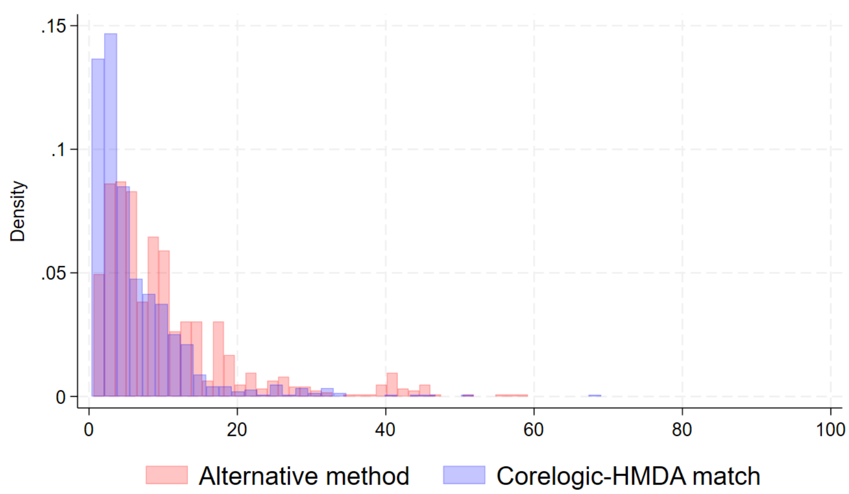
(a) White households



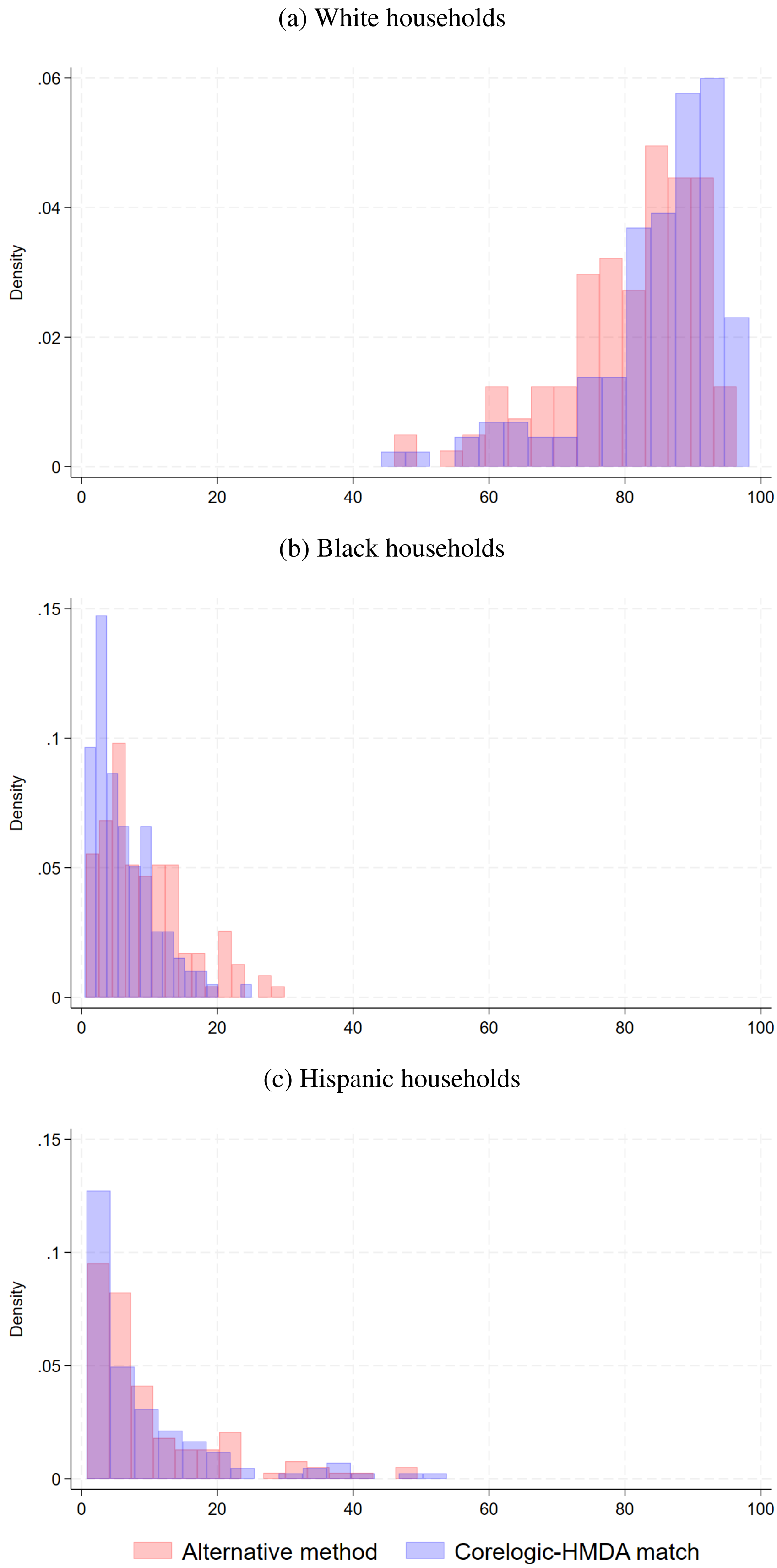
(b) Black households



(c) Hispanic households

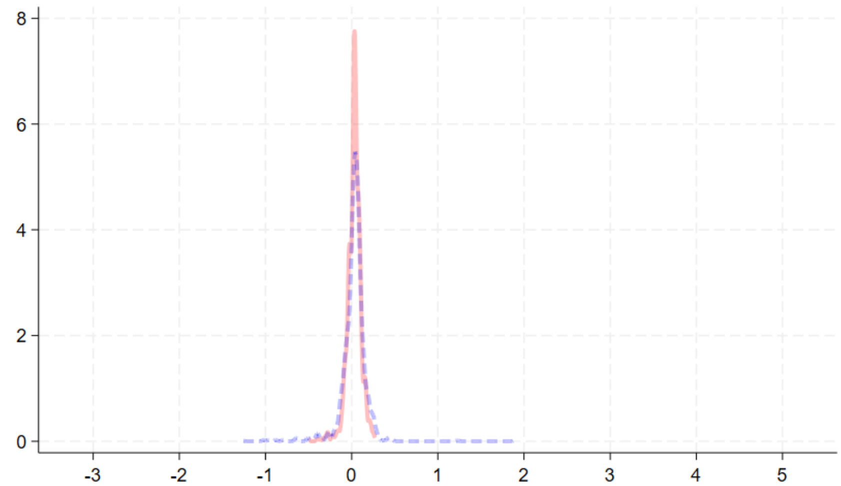


Appendix Figure C.2: Comparison of the Alternative Method and the CoreLogic–HMDA Method: Transaction Share (Percent) Distribution

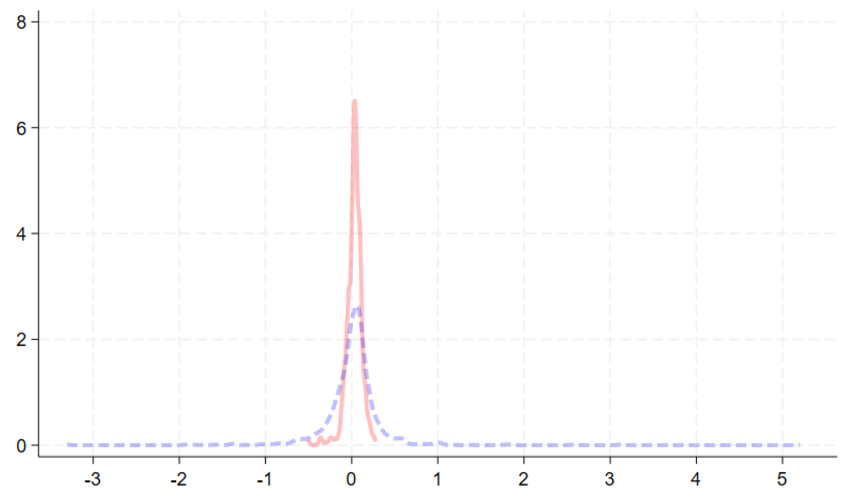


Appendix Figure C.3: Comparison of the Alternative Method and the CoreLogic–HMDA Method: Annual Change in Log HPI (Percent), Kernel Density

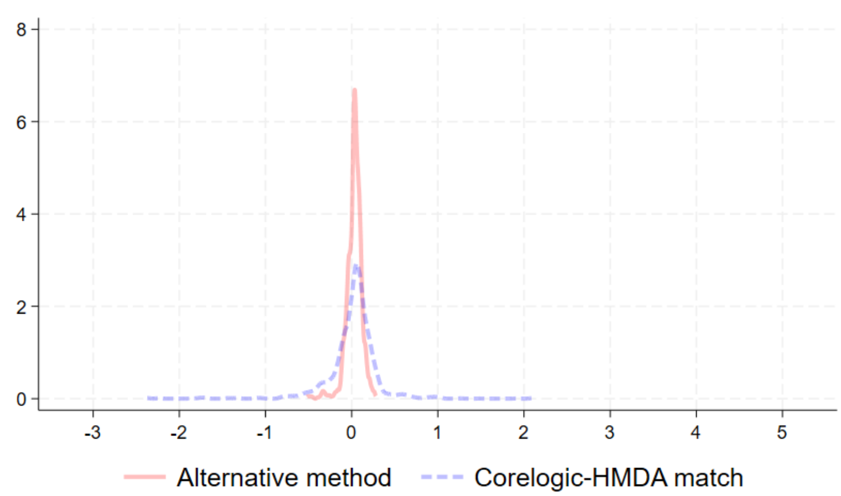
(a) White households



(b) Black households



(c) Hispanic households



Appendix D Features of the Monetary Policy Surprises

The impact of the Bauer and Swanson (2023)'s monetary policy surprises on the intraday changes of multiple financial market instruments on FOMC days are shown in Table D.1. These event-study regressions are of the form

$$y_t = \beta \mathrm{MP}_t + \text{constant} + u_t,$$

where t indexes monetary policy announcements, y_t is an asset return or an interest rate change, MP_t is a measure of the policy surprise, and both y_t and MP_t are measured over 30-minute windows around the announcement. The sample period is from 1989 to 2019. Variations in the number of observations across different columns arise from data availability, particularly in the earlier part of the sample period.

Appendix Table D.1: Effects of Bauer and Swanson (2023)'s Monetary Policy Surprises on the Financial Market

	(1) ED4	(2) Two-year Treasury Yield	(3) Five-year Treasury Yield	(4) Ten-year Treasury Yield	(5) SP500
MP	0.994***	0.740***	0.643***	0.412***	-5.570***
	(0.048)	(0.045)	(0.047)	(0.042)	(0.838)
Constant	-0.010***	-0.008***	-0.005***	-0.002	0.041
	(0.002)	(0.002)	(0.002)	(0.002)	(0.029)
Observations	322	258	307	322	322
R-squared	0.750	0.689	0.550	0.363	0.249

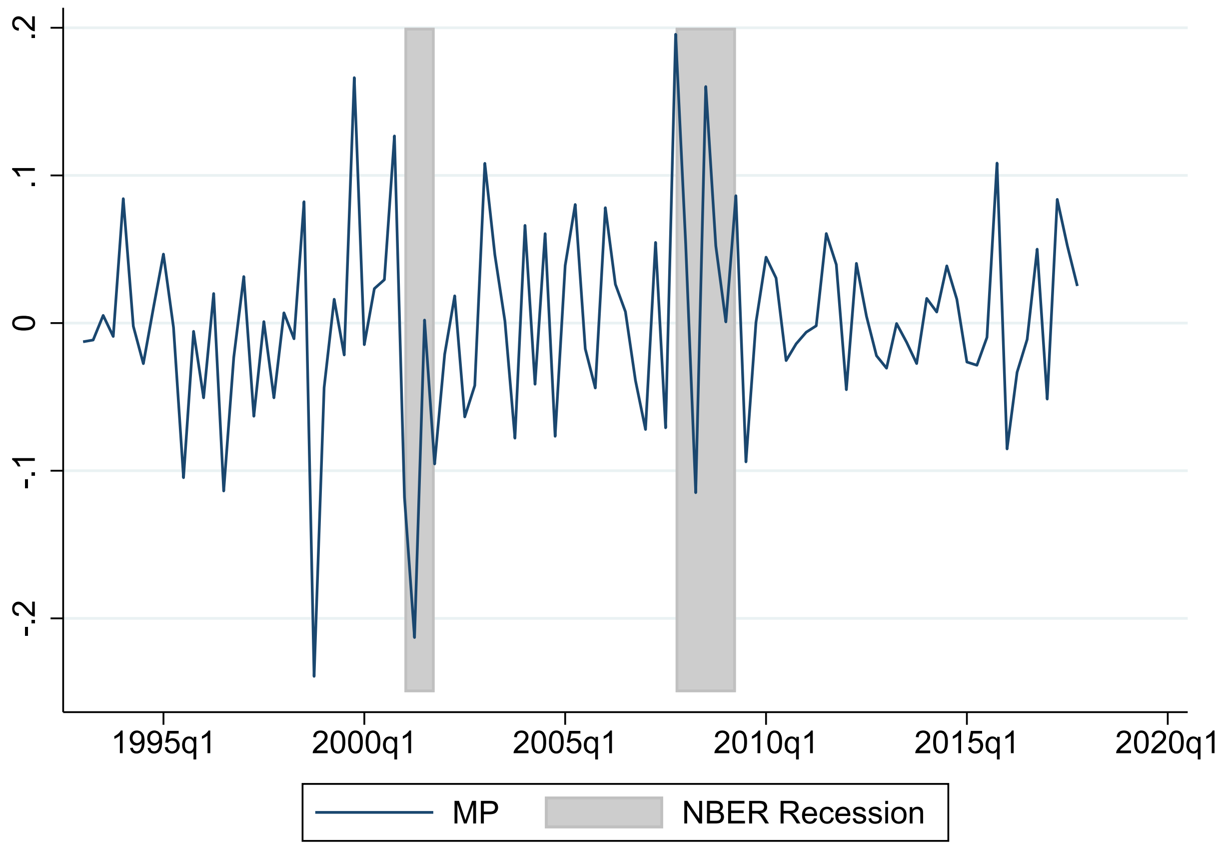
We also use an alternative monetary policy shock series as a robustness check. The data we use are changes in the interest rate of the current month federal funds futures (adjusted by the number of days that remain in the month relative to the total number of days), three-month-ahead federal funds futures, the second, third, and fourth Eurodollar futures (ED2, ED3, ED4), measured within 30-minute windows surrounding FOMC announcements. These instruments are used in Gürkaynak et al. (2005) and Nakamura and Steinsson (2018). The first principal component of the asset price responses is extracted. Similarly to Bauer and Swanson (2023), we normalize the shock series so that one unit of the monetary policy shock increases the intraday change in the fourth quarterly Eurodollar future rate by 100 basis points. Positive values correspond to contractionary monetary policy surprises. The impact of the shock on the intraday changes of multiple financial market instruments on FOMC days is shown in Table D.2. The sample period is from 1990 to 2018.

To obtain monetary policy shocks at quarterly frequencies, we assign each shock to the quarter in which the corresponding FOMC announcement occurs. The quarterly shock series are plotted in Figure D.1.

Appendix Table D.2: Effects of the Alternative Monetary Policy Surprises on the Financial Market

	(1) ED4	(2) Two-year Treasury Yield	(3) Five-year Treasury Yield	(4) Ten-year Treasury Yield	(5) SP500
Alternative MP	1.000***	0.929***	0.682***	0.356***	-4.891***
	(0.060)	(0.054)	(0.074)	(0.061)	(0.817)
Constant	-0.012***	-0.010***	-0.005*	-0.003	0.010
	(0.002)	(0.002)	(0.003)	(0.003)	(0.030)
Observations	258	240	240	240	257
R-squared	0.768	0.780	0.511	0.244	0.291

Appendix Figure D.1: Alternative Monetary Policy Surprises at Quarterly Frequency



Notes: This figure plots the quarterly series of alternative monetary policy surprises.

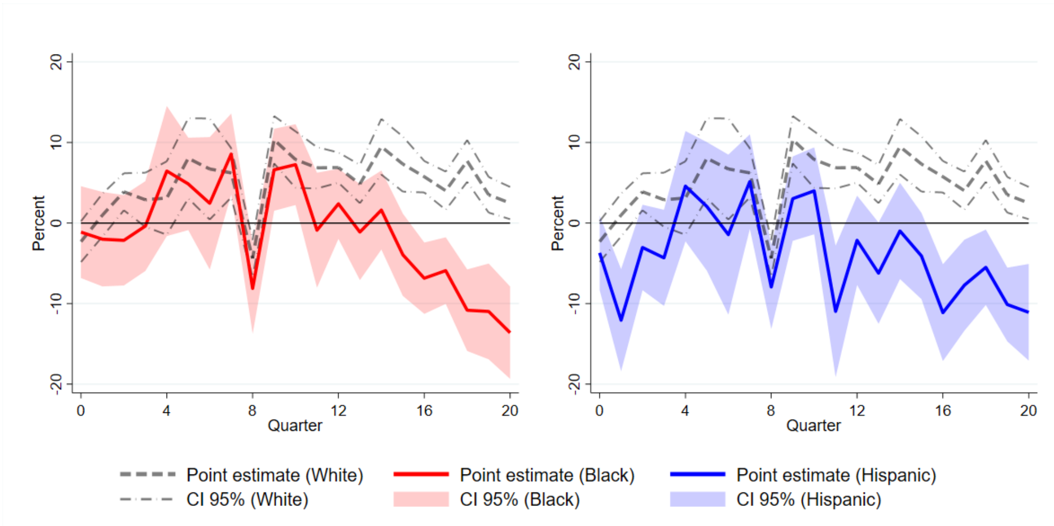
Appendix E Additional Results

Figure E.1 displays the impulse responses of the net purchase intensity and the cumulative (log) home price change to a 25-basis-point increase in the federal funds rate. We present the point estimates and confidence intervals for the coefficient of $0.25 \times \beta_y^{(h)}$ in equation (1).

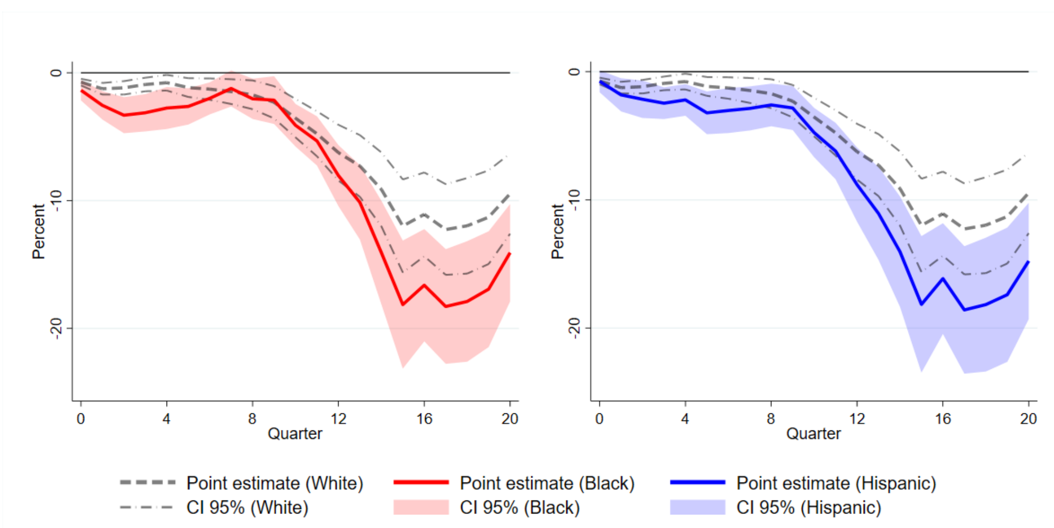
Additional results for section 4.1 can be found in Figures E.2, E.3, and E.4.

Appendix Figure E.1: Responses to Monetary Policy by Race

(a) Net purchase intensity



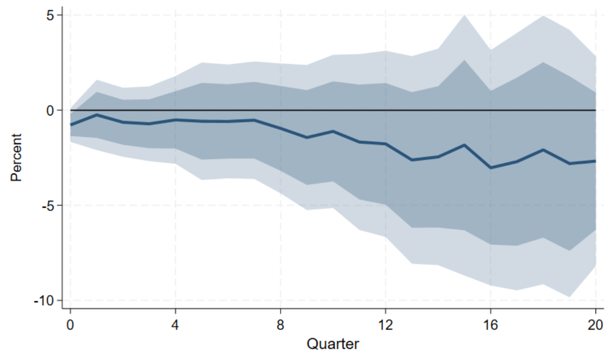
(b) Home price



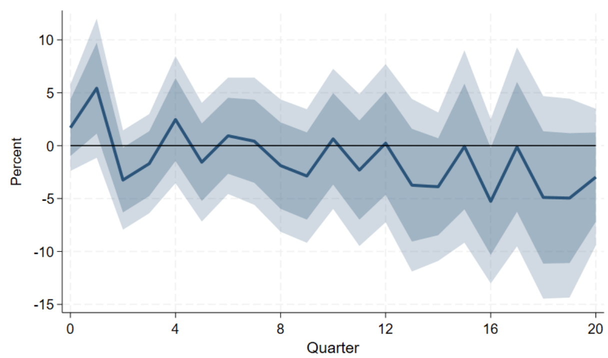
Notes: Panels (a) and (b) present the responses of the net purchase intensity and cumulative (log) home price change to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse responses for the Black (left) and Hispanic (right) racial groups, and compares them with the responses for the White racial group. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure E.2: Responses of Home Price for White, Black, and Hispanic Households: Mixed Neighborhoods Versus Predominantly White Neighborhoods

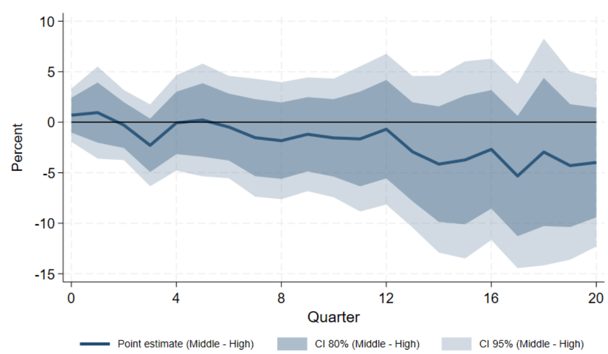
(a) White households



(b) Black households



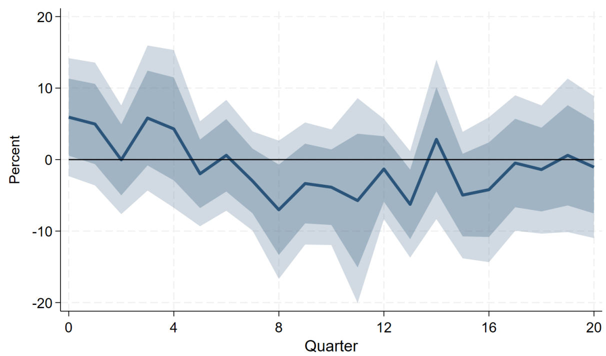
(c) Hispanic households



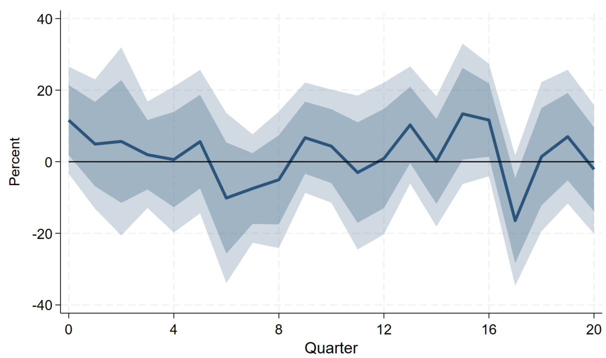
Notes: Panels (a), (b), and (c) show the differences in impulse responses of cumulative (log) home price changes to a 25-basis-point increase in the federal funds rate for White, Black, and Hispanic households, respectively. Each panel compares the impulse responses between neighborhoods with middle and high White population shares. Standard errors are clustered at the city level. The shaded areas represent the 80 percent and 95 percent confidence intervals.

Appendix Figure E.3: Responses of Net Purchase Intensity for White, Black, and Hispanic Households: Minority Neighborhoods Versus Predominantly White Neighborhoods

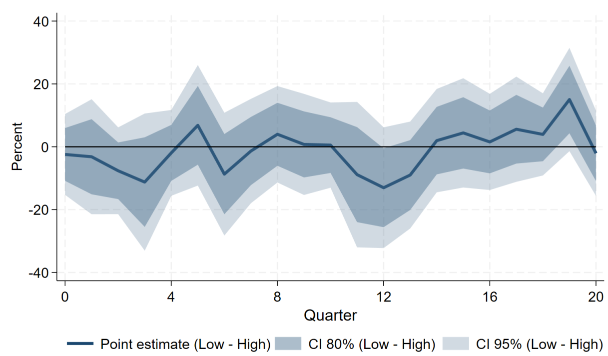
(a) White households



(b) Black households



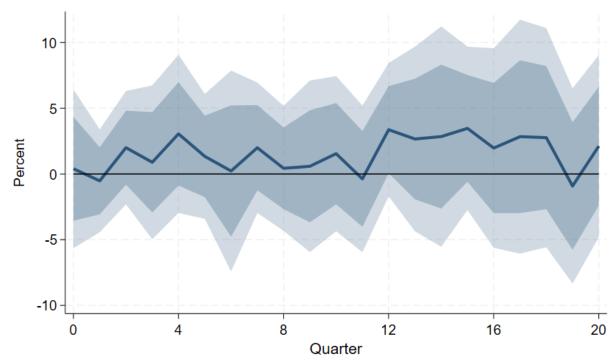
(c) Hispanic households



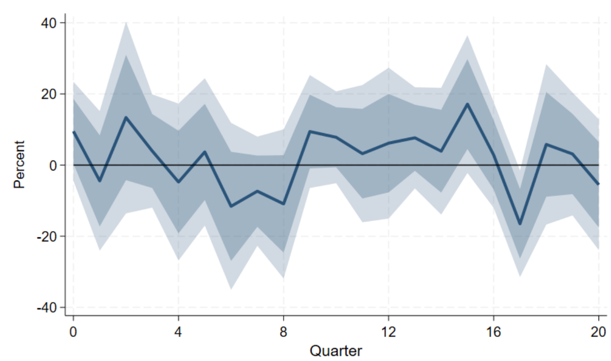
Notes: Panels (a), (b), and (c) show the differences in impulse responses of net purchase intensity to a 25-basis-point increase in the federal funds rate for White, Black, and Hispanic households, respectively. Each panel compares the impulse responses between neighborhoods with low and high White population shares. Standard errors are clustered at the city level. The shaded areas represent the 80 percent and 95 percent confidence intervals.

Appendix Figure E.4: Responses of Net Purchase Intensity for White, Black, and Hispanic Households: Mixed Neighborhoods Versus Predominantly White Neighborhoods

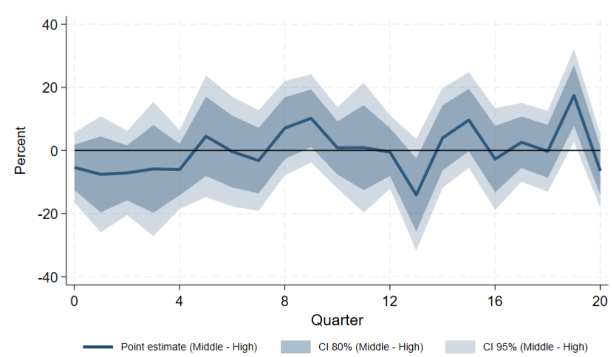
(a) White households



(b) Black households



(c) Hispanic households



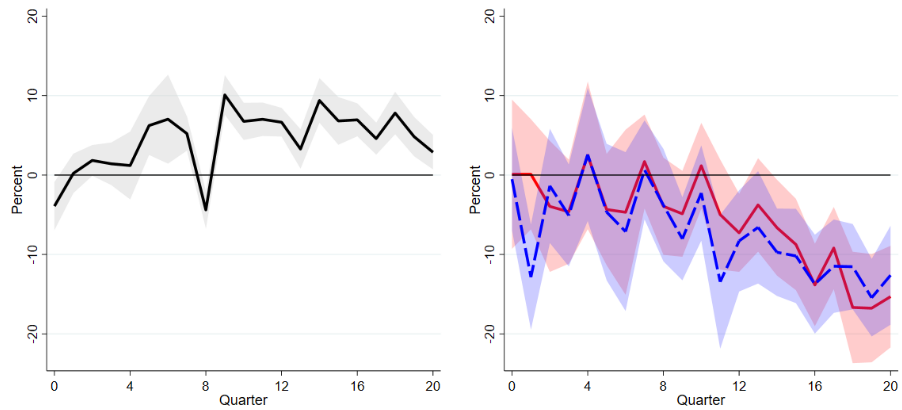
Notes: Panels (a), (b), and (c) show the differences in impulse responses of net purchase intensity to a 25-basis-point increase in the federal funds rate for White, Black, and Hispanic households, respectively. Each panel compares the impulse responses between neighborhoods with middle and high White population shares. Standard errors are clustered at the city level. The shaded areas represent the 80 percent and 95 percent confidence intervals.

Appendix F Robustness Checks

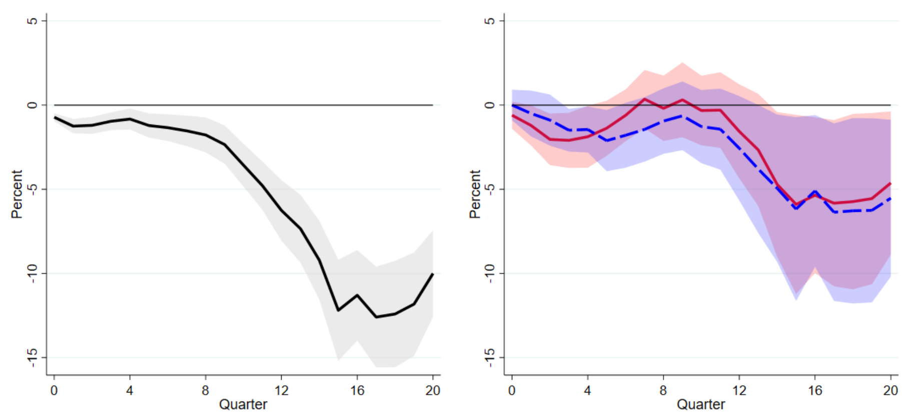
To ensure the robustness of our baseline results, we conduct several different robustness checks. These include using an alternative instrument for monetary policy, measuring net purchase intensity by focusing on dollar volumes of purchases and sales rather than counts, evaluating the impact on real home price appreciation, and testing an alternative specification incorporating quarterly changes in the federal funds rate, $\triangle i_t$. We also introduce additional controls to account for potential confounding factors, assess the results without city fixed effects, and add more variable lags. Moreover, we analyze unweighted results to validate our findings under different weighting assumptions and employ a reduced-form specification. These extensive checks affirm the robustness of our findings.

Appendix Figure F.1: Responses to Monetary Policy by Race, Net Purchase Volume Intensity

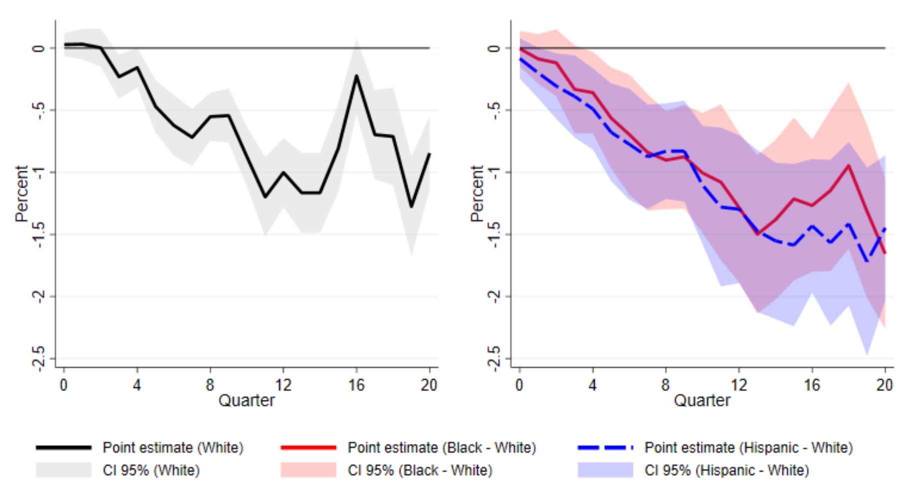
(a) Net purchase volume intensity



(b) Home price



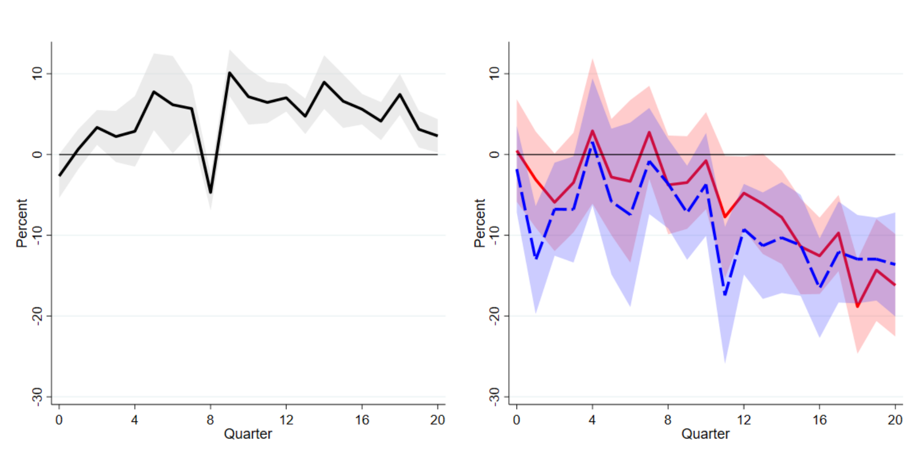
(c) Employment



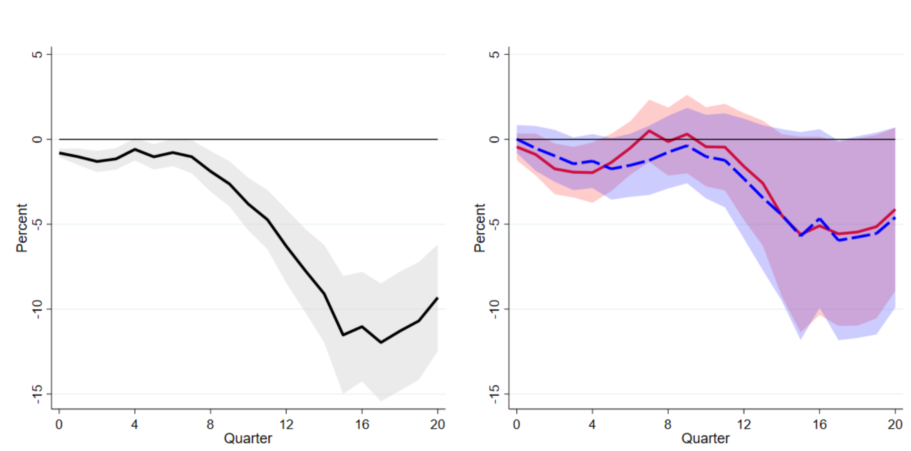
Notes: Panels (a), (b), and (c) represent the responses of net purchase volume intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.2: Responses to Monetary Policy by Race, Real HPIs

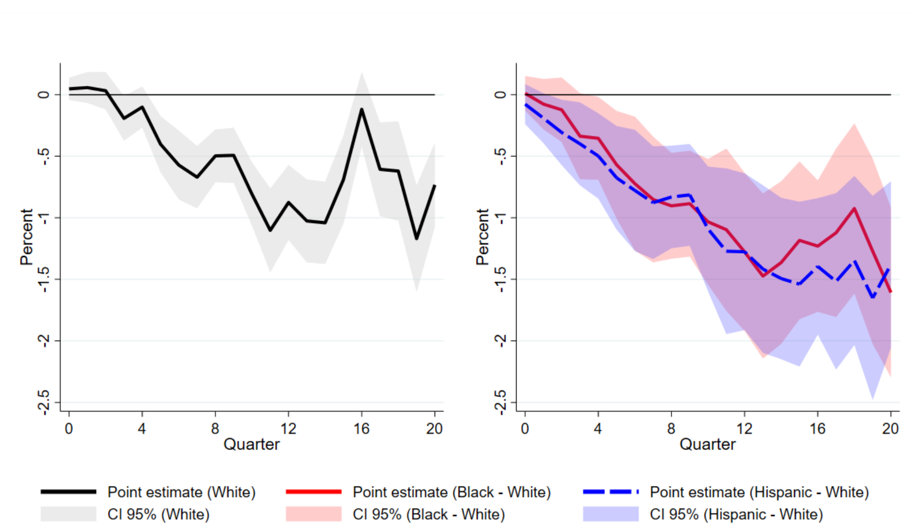
(a) Net purchase intensity



(b) Real home price



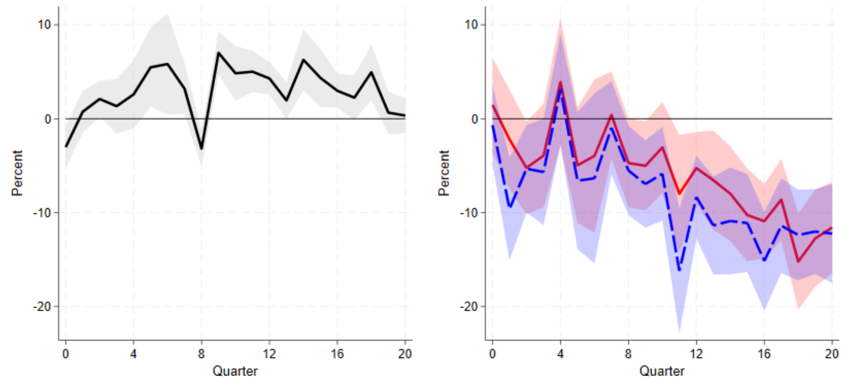
(c) Employment



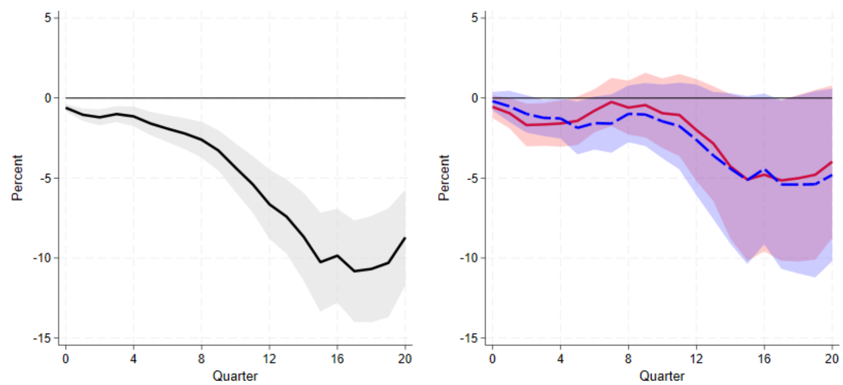
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) real home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.3: Responses to Monetary Policy by Race, alternative specification with $\triangle i_t$

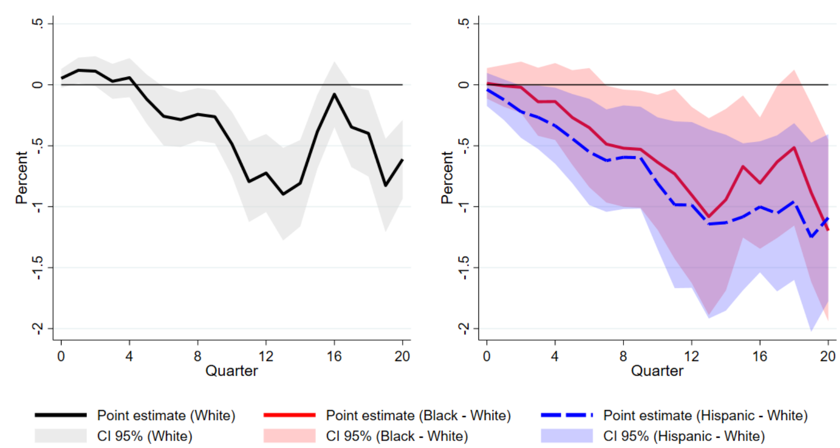
(a) Net purchase intensity



(b) Home price



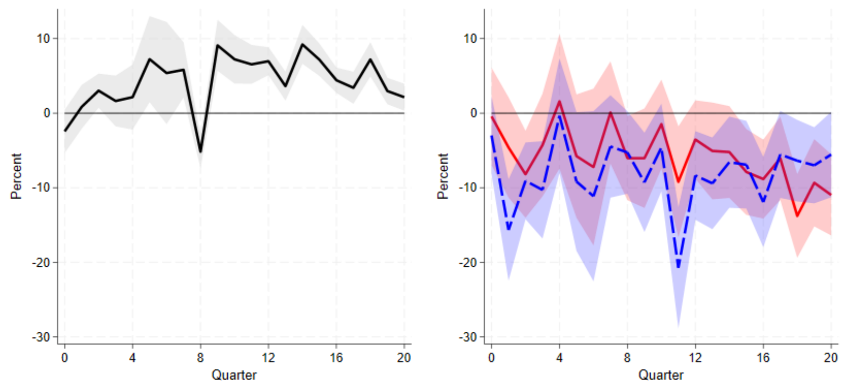
(c) Employment



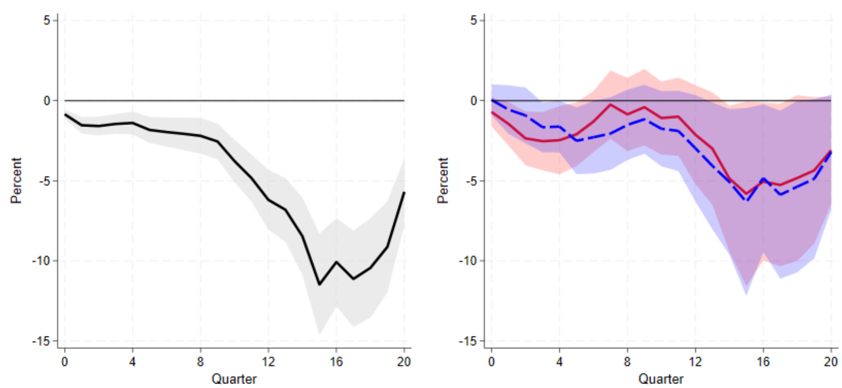
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate change, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.4: Responses to Monetary Policy by Race, With Additional Controls (Population Share by Race, Unemployment Rates, Lender Competitiveness)

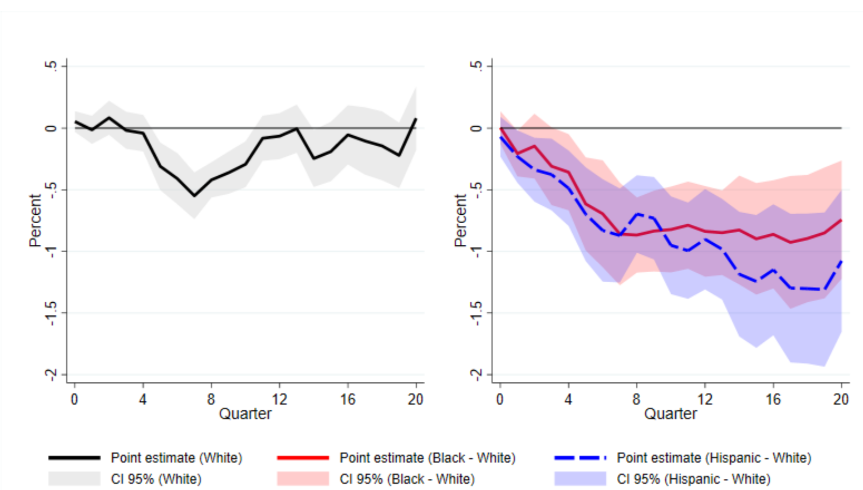
(a) Net purchase intensity



(b) Home price



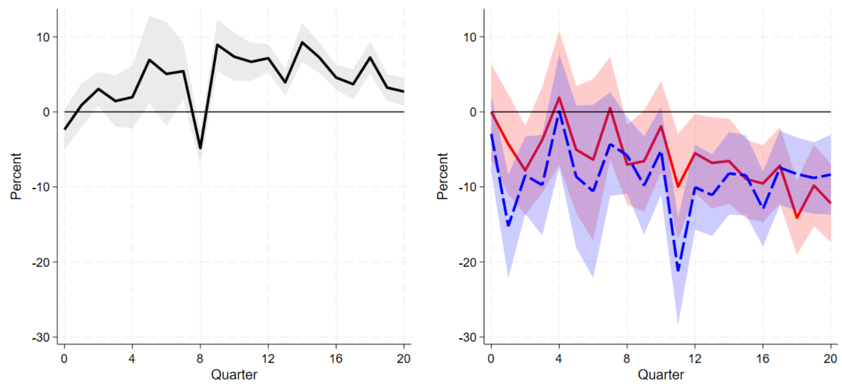
(c) Employment



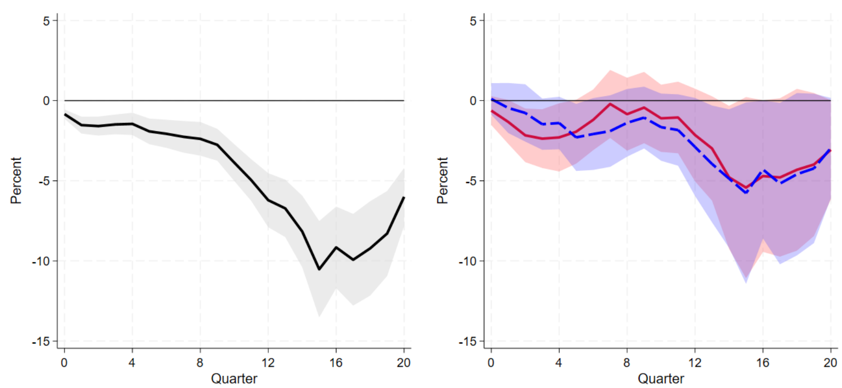
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.5: Responses to Monetary Policy by Race, With Additional Controls (Population Share by Race, Unemployment Rates, Lender Competitiveness, LTV by Race, FHA Share by Race)

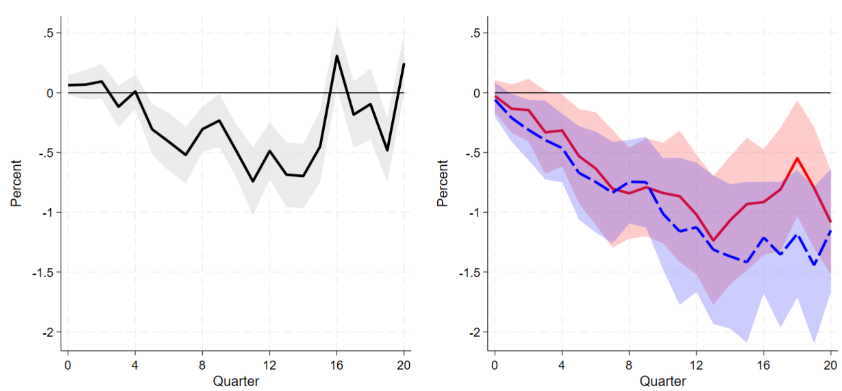
(a) Net purchase intensity



(b) Home price



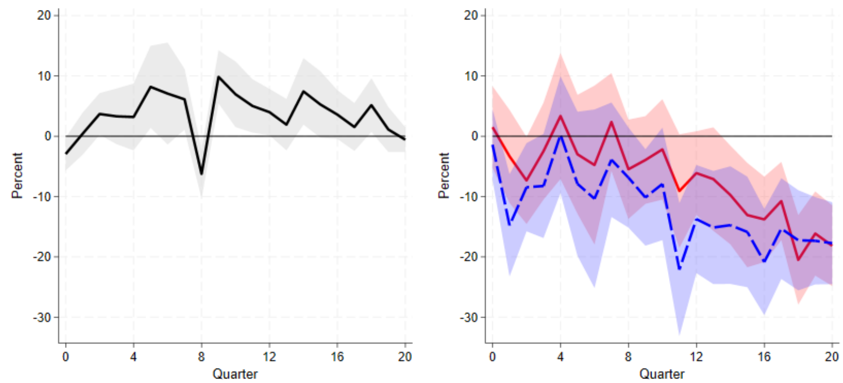
(c) Employment



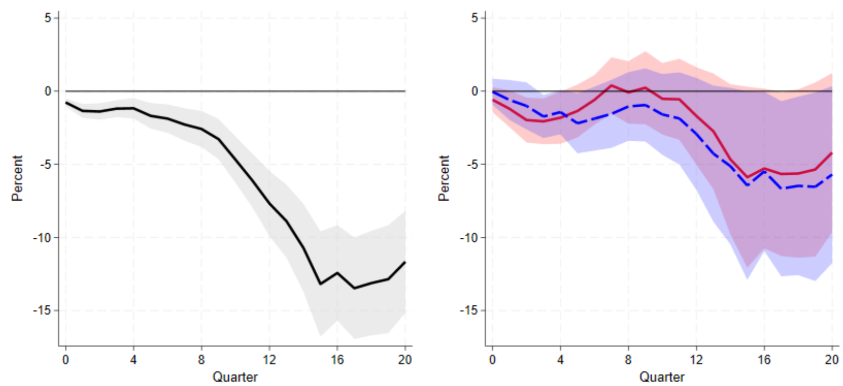
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.6: Responses to Monetary Policy by Race, Without City Fixed Effects

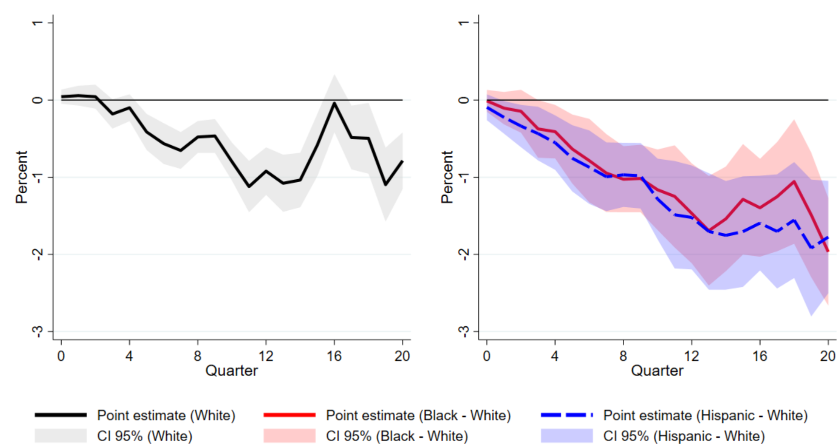
(a) Net purchase intensity



(b) Home price



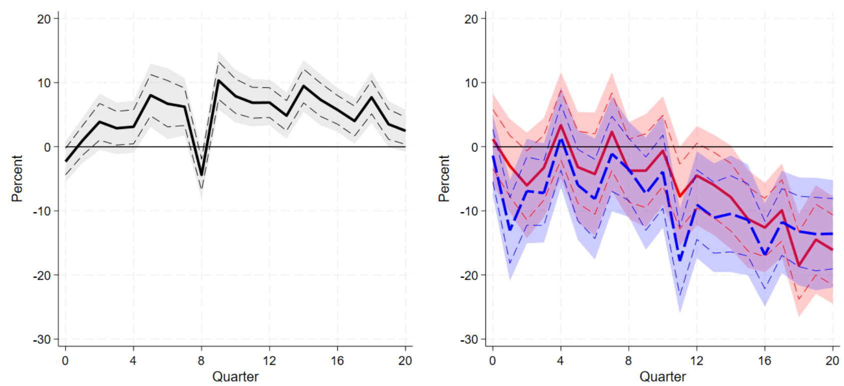
(c) Employment



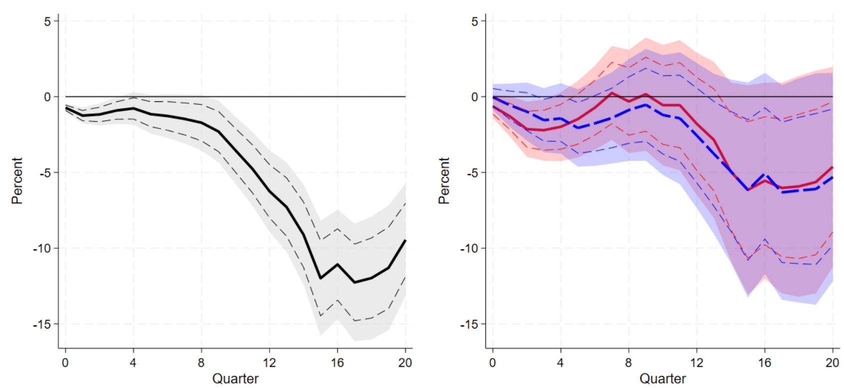
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.7: Responses to Monetary Policy by Race, Alternative Standard Errors

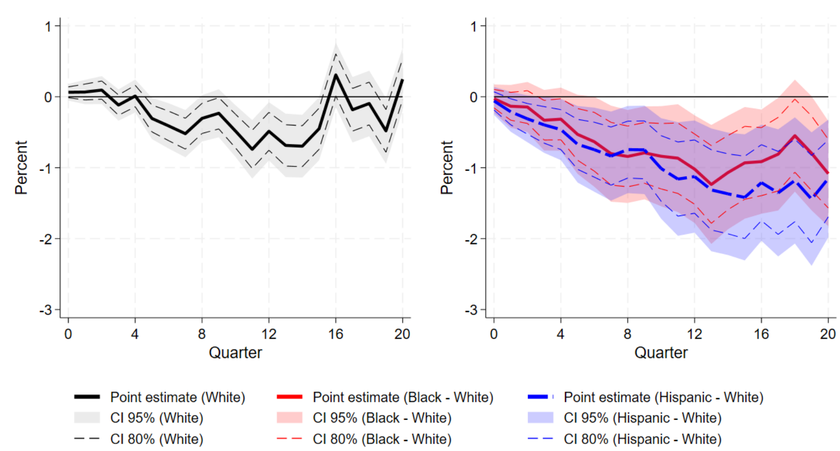
(a) Net purchase intensity



(b) Home price



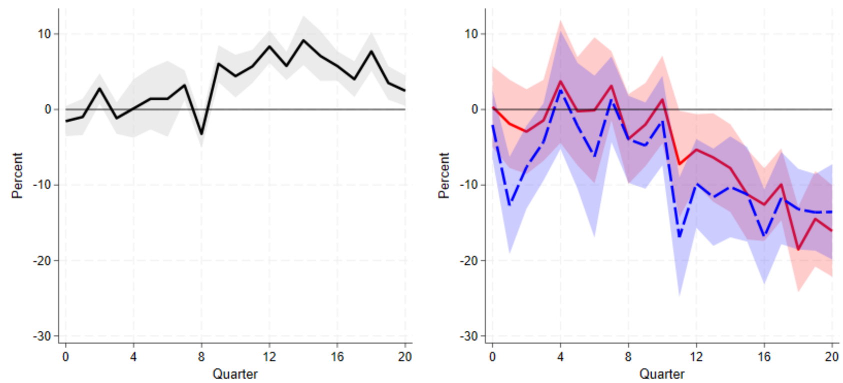
(c) Employment



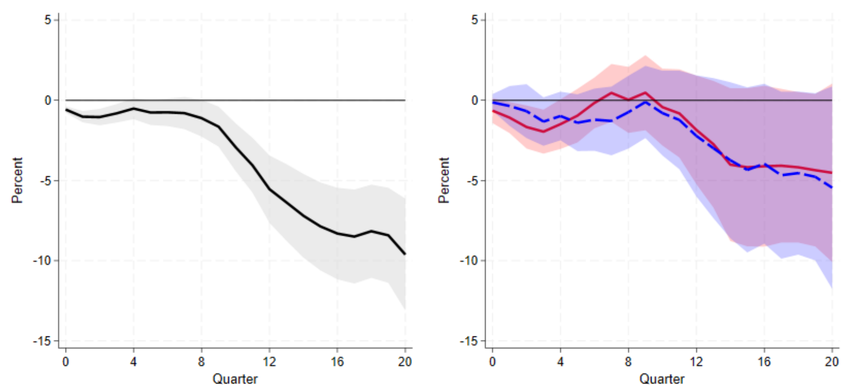
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. We use heteroskedastic and autocorrelation consistent (HAC) standard errors. The 80 percent and 95 percent confidence intervals are represented.

Appendix Figure F.8: Responses to Monetary Policy by Race, Time Variation (1995–2013)

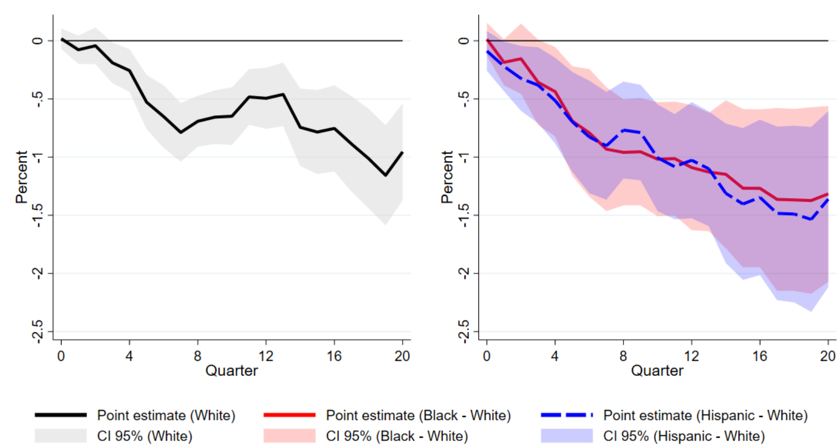
(a) Net purchase intensity



(b) Home price



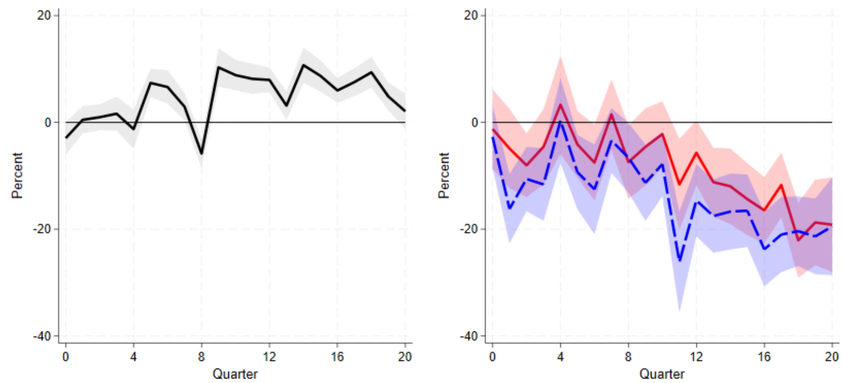
(c) Employment



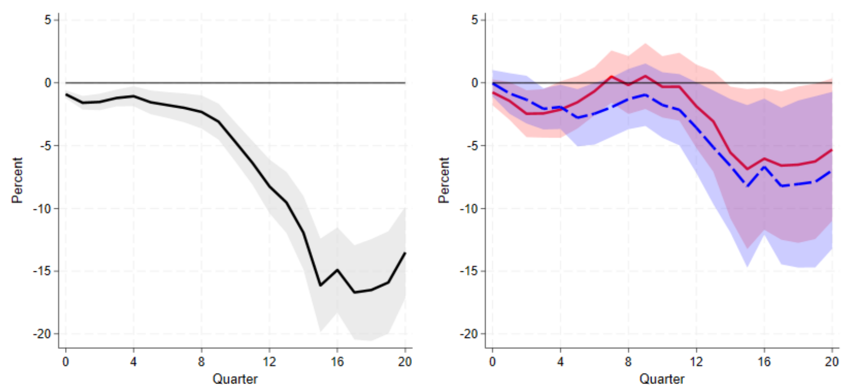
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.9: Responses to Monetary Policy by Race, Time Variation (2000–2017)

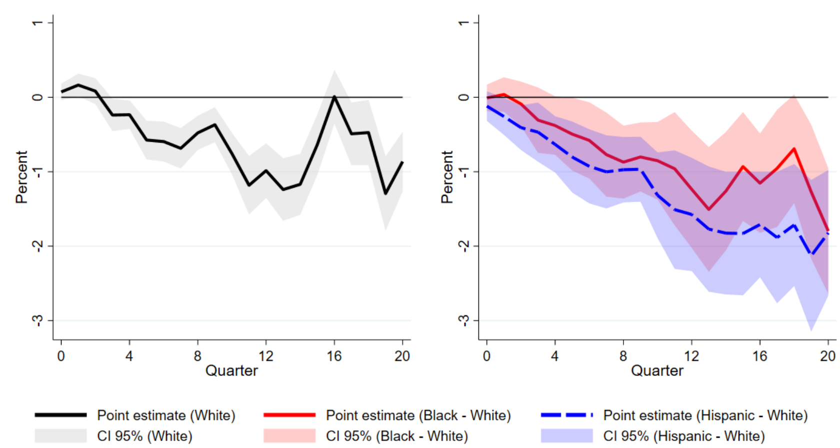
(a) Net purchase intensity



(b) Home price



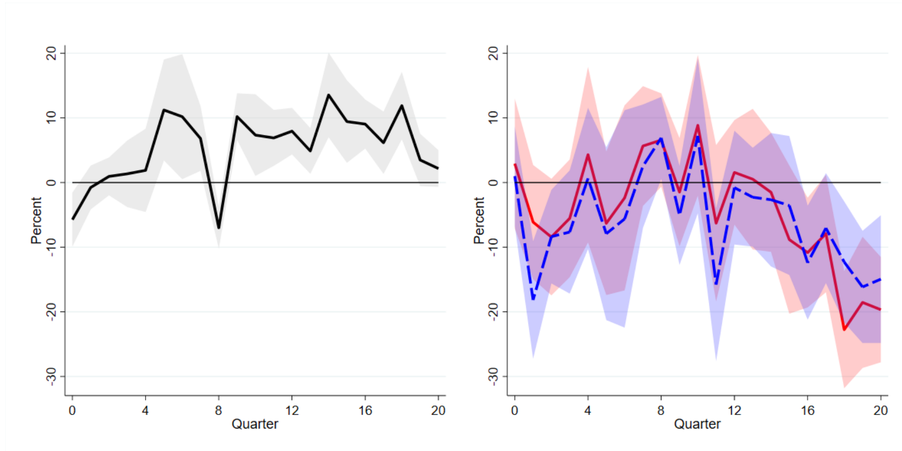
(c) Employment



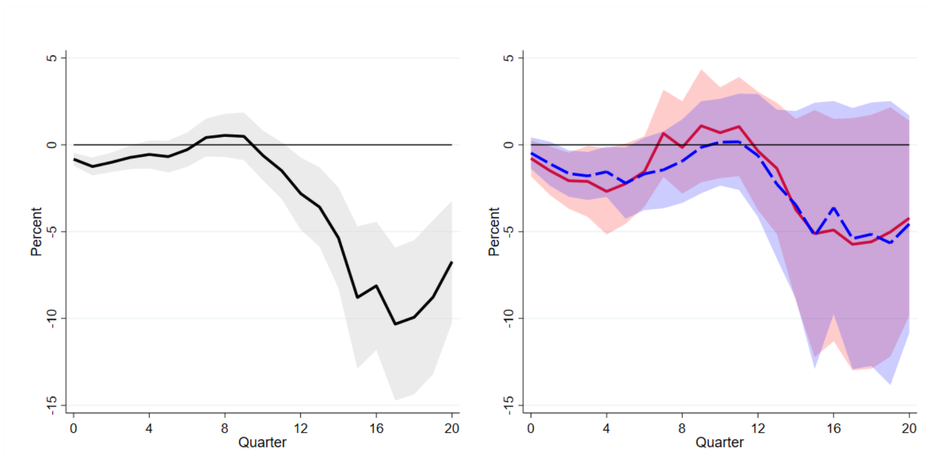
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.10: Responses to Monetary Policy by Race, Time Variation (Excluding 2008 and 2009)

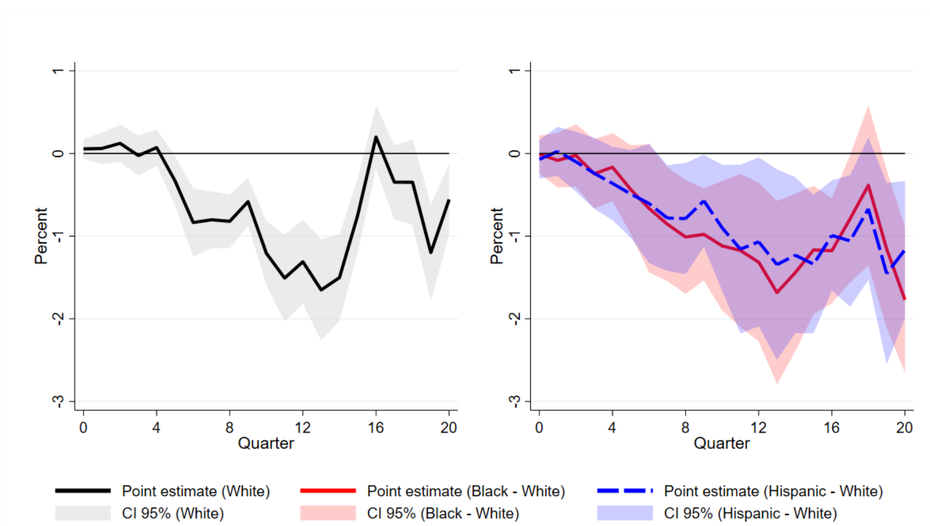
(a) Net purchase intensity



(b) Home price



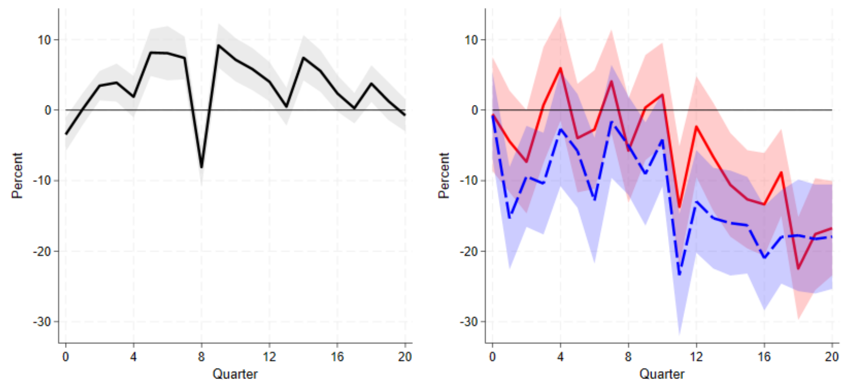
(c) Employment



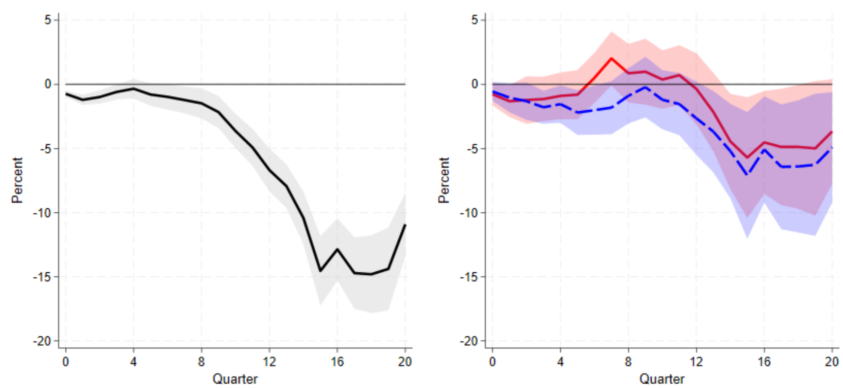
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.11: Responses to Monetary Policy by Race, Unweighted

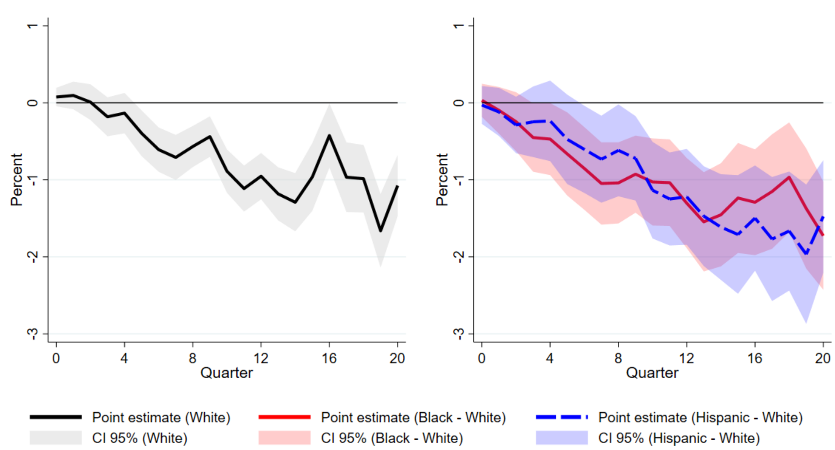
(a) Net purchase intensity



(b) Home price



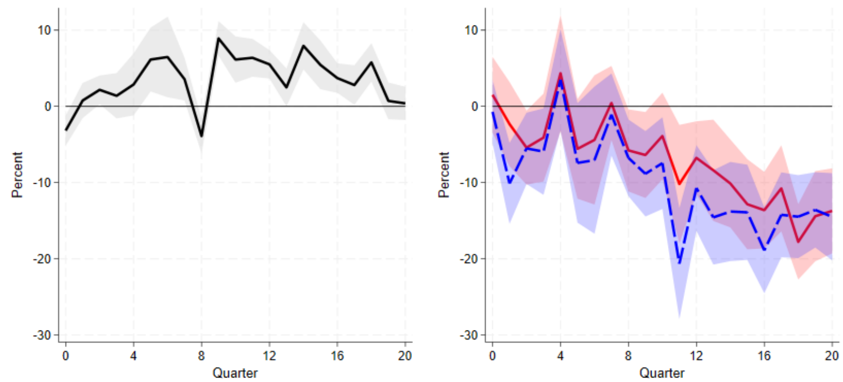
(c) Employment



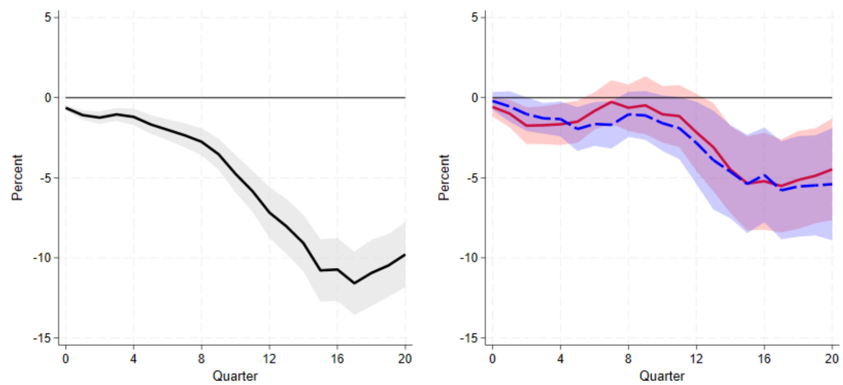
Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the federal funds rate, respectively. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.

Appendix Figure F.12: Responses to Monetary Policy by Race, Reduced-Form

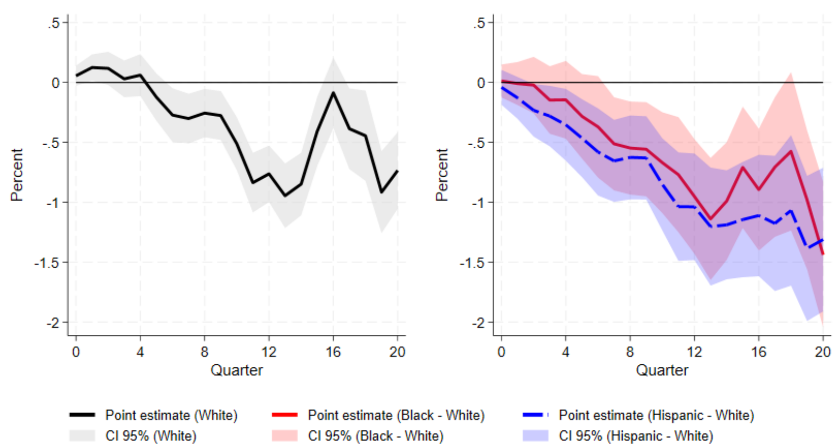
(a) Net purchase intensity



(b) Home price



(c) Employment



Notes: Panels (a), (b), and (c) represent the responses of net purchase intensity, cumulative (log) home price change and cumulative employment growth to a 25-basis-point increase in the monetary policy surprises, respectively. The monetary policy surprise series are normalized such that a 25-basis-point increase in the surprise corresponds to a 25-basis-point change in the intraday fluctuations of the fourth quarterly Eurodollar future rate. Each panel depicts the impulse response of White households on the left side. On the right side, the differences in impulse responses between Black and White households (solid red line) and between Hispanic and White households (dashed blue line) are plotted. Standard errors are clustered at the city level. The 95 percent confidence intervals are represented by the shaded areas.