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The Impacts of Racial Differences in Economic Challenges on Housing, Wealth, and Economic Security Among OASI Beneficiaries

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Abstract

Housing wealth comprises 40 percent of the net wealth of retirement-age Americans, 43 percent of whom have not yet paid off their mortgages. This report analyzes two research questions. First, we evaluate the extent to which Old-Age and Survivors Insurance (OASI) benefits advance economic security and racial equity among homeowners. Our use of linked administrative data facilitates a comparative analysis of economic well-being measures before and after homeowners became eligible for OASI benefits. Second, we analyze how racial disparities in job losses during working years contribute to racial differences in economic security at retirement, focusing particularly on exposure to distressed home sales. Utilizing confidential taxpayer microdata, we assess racial discrepancies in the incidence of job loss, distressed sales, and wealth destruction due to distressed sales. Our findings imply that racial/ethnic differences in wealth at retirement are at least partly attributable to differences in labor market experiences. In terms of policy implications, our findings provide support for policies that mitigate employment and income instability during working years. Such policies are likely to have effects that accumulate throughout the life cycle and can mitigate racial/ethnic differences in wealth at retirement.

Keywords: housing wealth, income volatility

JEL Codes: D6, G5, J7

1 Introduction

A large racial wealth gap has been documented in the US for as long as data has been available (Kuhn et al. 2020; Derenoncourt et al. 2021). The racial wealth gap extends to gaps in wealth and economic security at retirement (Munnell et al. 2018; Hou and Sanzenbacher 2021). Despite an expanding set of empirical research on this issue, our understanding of the causes and consequences of this gap remains limited. This report analyzes racial disparities in housing-related outcomes among OASI beneficiaries, with a particular focus on the role of income instability during working years.

Our focus on housing-related outcomes is motivated by a recognition of the importance of housing wealth to retirement security. Housing forms 40 percent of net wealth for retirement-age Americans, 43 percent of whom have not yet paid off their mortgages (Panel Study of Income Dynamics 2001–2017; American Community Survey 2003–2017). These same households face increasing economic barriers: as of 2018, 12.2 percent of bankruptcy filers were 65 or older, up from 2.1 percent in 1991 (Bernard 2018).

These patterns imply that disparities in housing wealth are likely to have significant effects on retirement security. In prior work (Kermani and Wong 2021), we document the existence of large racial gaps in housing returns, seemingly generated by racial difference in income instability and illiquidity. These preliminary results suggest that together, racial differences in housing returns and homeownership can explain half of the racial difference in primary housing wealth at retirement. While the prior work points to the importance of disparities in the housing market during working years, it leaves open the question of how large are housing-related disparities at retirement, as well as the quantitative importance of disparities in the labor market for generating disparities at retirement.

Motivated by these unanswered questions, our research has two primary aims. Our first aim is to determine the extent to which OASI benefits promote economic security and racial equity among homeowners. We use a novel administrative data linkage housed at the UC Berkeley Fisher Center for Real Estate and Urban Economics to compare measures of economic well-being before and after homeowners become eligible for OASI benefits, including distressed sales and housing instability. Our second aim is to measure the extent to which racial differences in job losses during working age contribute to racial differences in economic security at retirement through exposure to distressed sales. Confidential taxpayer microdata held by the US Census allows us to simultaneously measure racial differences in the incidence of job loss and distressed sales. This report summarizes the results of a first year of work, which will directly contribute to an expanded set of analyses in a second year of work.

This study advances on prior work by analyzing novel administrative data sources, whereas prior work has largely relied on survey-based data. For instance, Ritter and Taylor (2011) use data from the National Longitudinal Survey of Youth to document that Black workers have higher rates of unemployment, and Morduch et al. (2019) use the Panel Study of Income Dynamics to show that income volatility has increased for Black households. Similar studies have used the Current Population Survey (Couch et al. 2018; Wrigley-Field and Seltzer 2020). Survey-based data sources are inherently limited because the self-reported

measures of income and employment entail substantial measurement error. Moreover, surveys do not capture the wealth-destroying effects of foreclosures because they typically elicit the value of respondents' homes in a non-foreclosure sale, and they generally do not ask respondents about the outcomes of prior foreclosures. The administrative data sources used in this proposal overcome these limitations. We use highly accurate measures of income and employment from tax records, and we can observe distressed sales in administrative property records. We are also able to analyze a broad range of measures of economic well-being at retirement that are not captured in survey data, including distressed sales, bankruptcy, and migration.

The remainder of this report is divided in two sections. Section 2 analyzes measures of economic well-being among OASI beneficiaries with a particular focus on racial/ethnic disparities. This section makes use of the data housed at the UC Berkeley Fisher Center. Section 3 analyzes racial differences in income instability and their relation to observed gaps in economic well-being using administrative records held by the US Census Bureau. Section 4 concludes with implications for future research in this agenda.

2 OASI Benefits and Economic Well-Being

This section analyzes measures of economic well-being among OASI beneficiaries, as well as racial and ethnic disparities in well-being. We use a novel linked administrative dataset and find that while economic security generally improves in retirement years, there is no evidence of a discrete change in well-being upon eligibility for OASI benefits. Moreover, racial and ethnic disparities persist throughout retirement age.

2.1 Data

We use a series of linked administrative data sources to measure outcomes for our study population. Our linked analysis data builds on the dataset developed in Kermani and Wong (2021). Below we reproduce a description of these data and discuss the additional use of voter registration data for the present analysis.

Estimating actual housing returns necessitates the examination of both the buying and selling prices. To facilitate this, we utilize a large-scale panel dataset comprising millions of residential properties, which includes records of transactions and mortgages. This dataset is compiled by ATTOM, a private data aggregator, and is sourced from local government records. We refer to this dataset as the "property records."

Data on homeowners' racial and ethnic identities is obtained from the Home Mortgage Disclosure Act (HMDA) data. Legislation mandates that lenders disclose specific information about new mortgage loans, such as the self-reported race and ethnicity of loan applicants, and their income. With the exception of mortgages issued by small financial institutions exempted from these reporting requirements, this data encompasses virtually all mortgage originations since the 1990s.

The property records, which associate mortgages with properties, are integrated with the HMDA data by aligning the year of mortgage origination, Census tract, monetary amount, and lender name. This method of linkage is comparable to those implemented in prior studies. We restrict our attention to HMDA mortgages unique in terms of the year, Census tract, amount, and lender name, necessitating an exact merge based on the year, tract, transaction amount, and a fuzzy string match on the lender name. The administrative data linkages for this study were carried out by the Fisher Center for Real Estate and Urban Economics at UC Berkeley.

To calculate the rate of return for a specific ownership period, we create an algorithm that detects repeat sales of properties. We pinpoint property purchases by focusing on arm's length, full-consideration transactions. Future sales of the property are identified by selecting the subsequent arm's length, full-consideration transaction of the same property. We establish name similarity measures to verify that the buyer in the initial transaction is identical to the seller in the subsequent transaction. More information about this algorithm is provided in the appendix.

Our main sample for analysis consists of owner-occupied properties where we can observe a purchase and sale price along with the buyer's race or ethnicity. We call this sample the "repeat-sales sample," and it is limited to homes bought with a mortgage. While we can observe cash purchases and calculate subsequent returns, it is not possible to determine self-reported homeowner race or ethnicity for these transactions. This is because the HMDA records containing race/ethnicity information are only available for purchases made with a mortgage.

We construct the repeat-sales sample from 132 million arm's length home purchases recorded in the property data from 1990 to 2021. We identify 27.0 million ownership spells where we can observe a purchase and sale price, with the purchase taking place on or before 2016. We are able to link 11.3 million of these ownership periods to HMDA purchases made between 1990 and 2016.[1] We exclude transactions with prices less than $10,000, combined loan-to-value ratios exceeding 102.5 percent, and ownership spells lasting fewer than 12 months or with sales after March 2020. This results in a sample of 10.0 million spells. Limiting our data to Black, Hispanic, and White owner-occupant households gives us our analysis sample of 7.1 million ownership periods between January 1990 and March 2020. Additional details can be found in Kermani and Wong (2021).

We advance over the data constructed in Kermani and Wong (2021) by incorporating voter registration records that contain homeowner date of birth. These data were provided by Aristotle and linked to the main analysis sample by the Fisher Center. Records were linked by address and homeowner name before constructing a de-identified dataset of ownership spells for analysis. This linkage yields 6.5 million ownership spells, of which 1.1 million terminated in a sale by 2020. For the analysis we conduct in this report, we proxy for OASI status by homeowner age using date of birth recorded in the voter registration records. Table 1 presents summary statistics for our merged sample.

[1]The merge between the property records and the HMDA records covers purchases through 2016, while the property records include sales through 2020.

Table 1: Summary Statistics

Variable	Mean	SD	p10	p90
Black	0.067248	0.250451	0	0
Hispanic	0.079345	0.270276	0	0
White	0.708711	0.454356	0	1
Asian	0.049294	0.216482	0	0
Income	99.20532	111.0112	37	172
Purchase Year	2009.512	4.925808	2003	2016
Purchase Amount	309819.5	1138825	112500	559100
CLTV	85.62272	15.74322	65.21739	100
Age at Purchase	40.83017	11.79815	27	58
Sale Year	2019.106	2.477993	2016	2020
Annual Rate of Return	3.420743	3.803791	0.252999	7.325617
Age at Sale	50.42459	12.62872	35	68
Distressed Sale	0.032335	0.176887	0	0
Any Sale	0.173927	0.379047	0	1

Notes: This table presents summary statistics from our sample merged to the voter records. CLTV denotes combined loan-to-value at purchase. Property-level variables from ATTOM property records. Homeowner age derived from Aristotle voter registration data. All other homeowner demographics from HMDA mortgage records. Dynamic outcomes reflect yearly rates. N= 6,498,410.

2.2 Levels of Economic Well-Being Among OASI Beneficiaries

We use our merged administrative data to conduct a descriptive analysis of three measures of economic well-being among OASI beneficiaries. The three measures of economic well-being are an indicator that a homeowner experienced a distressed sale (i.e., foreclosure or short sale), an indicator that a homeowner sold their home (and thus moved to another location), and annual realized housing returns. We follow the approach developed in Kermani and Wong (2021) to measure annual housing returns. In particular, we compute the annual unlevered rate of return for owner i, r_i^u using the following formula:

$$1 + r_i^u = \left(\frac{P_{i1}}{P_{i0}}\right)^{\frac{1}{T_{i1}-T_{i0}}}$$

In the above, P_{i0} and P_{i1} denote the property purchase and sale prices, while $T_{i1} - T_{i0}$ denotes the length of the ownership spell in years. Since property purchase and sale prices and dates are recorded in the property data, this measure of housing returns is straightforward to compute.

We conduct a descriptive analysis of these three outcomes, separately by race and ethnicity by plotting average values of these outcomes by age. Figure 1 presents the results of this exercise. We find that Black, Hispanic, and Asian OASI beneficiaries all appear to exhibit lower returns than White homeowners (Panel A). Interestingly, there is some evidence that these differences diminish in later years (i.e., by age 75). This is largely driven by average returns increasing for older homesellers.

In contrast, minority OASI beneficiaries who are homeowners appear to exhibit relatively lower rates of displacement relative to their White counterparts (Panel C). This is especially the case for Black homeowners, who exhibit annual sale rates of about 0.6 percent, compared to around 1.2 percentage points for Hispanic and Asian beneficiaries, and 1.3 percentage points for White beneficiaries. However, minority beneficiaries appear to exhibit higher rates of distressed sales than White homeowners (Panel E). While distressed sale rates appear to diminish with age for all groups, there is little evidence of convergence in racial/ethnic gaps in distressed sales at later ages.

2.3 Impact of OASI Benefits on Financial Security of Homeowners

We estimate the impacts of eligibility for OASI benefits on the financial security of homeowners by comparing differences in the aforementioned outcomes (i.e. distressed sales, housing stability, and housing returns) for homeowners just above and below the age of eligibility for OASI benefits. While the results in Figure 1 provide little visual evidence of a substantial trend discontinuity in these outcomes, it remains possible that factors we did not control for obscure such a discontinuity. Table 2 estimates a regression discontinuity specification using local linear regression for the incidence of property sales around age 62 (Panel A) and the full retirement age based on homeowner birth year (Panel B). Consistent with the

visual evidence, we find no evidence of a discontinuity at retirement, implying that housing instability changes little at retirement. Table 3 estimates similar results for any distressed sale (i.e., foreclosure or short sale) and finds similar results. Lastly, we analyze changes in realized returns around sale age in Table 4, and find no evidence of a discontinuity in realized returns.

Table 2: Discontinuity in Any Sale Around Retirement

	(1) Pooled	(2) Hispanic	(3) Black	(4) White	(5) Asian
Panel A. Age 62					
RD Estimate	0.0643**	0.0201	–0.0162	0.0803***	0.122
	(0.0250)	(0.0740)	(0.0560)	(0.0292)	(0.112)
Observations	13,251,731	790,695	989,732	9,725,661	467,617
Clusters	4.257e+06	426663	426212	3.227e+06	174447
Outcome mean	0.897	0.834	0.470	0.938	0.904
Panel B. Full Retirement					
RD Estimate	0.0641**	0.101	0.0390	0.0655*	0.124
	(0.0322)	(0.106)	(0.0738)	(0.0378)	(0.143)
Observations	8,835,844	487,486	632,884	6,600,593	274,026
Clusters	3.103e+06	214561	306469	2.222e+06	112318
Outcome mean	0.966	0.895	0.484	1.009	0.974

Notes: This table presents regression discontinuity estimates of an indicator that a homeowner sells their property in a given year around retirement age. Panel A analyzes the discontinuity around age 62, while Panel B analyzes the discontinuity at full retirement age, which varies by birth year. Outcomes have been multiplied by 100 for legibility. Standard errors in parentheses. All specifications include fixed effects that interact county and purchase year.

To complement these results estimated separately by race/ethnicity, we also explore additional dimensions of heterogeneity. Table 10 tests for differences in property sales, splitting the sample by income at mortgage origination, combined loan-to-value ratio at purchase, and debt-to-income ratio at mortgage origination. While the regression discontinuity estimator yields some statistically significant differences, these are not consistent between age 62 and the age of full retirement. Therefore, we conclude that there is little indication that the estimated null effects mask meaningful effects among large subgroups.

In additional results, we leverage the changes in eligibility age that have occurred during our sample window by estimating differences-in-differences specifications around the age cutoff for full benefit eligibility age cutoffs. Specifically, for individual i at age (in months) t, we estimate regressions of the following form:

Table 3: Discontinuity in Any Distressed Sale Around Retirement

	(1) Pooled	(2) Hispanic	(3) Black	(4) White	(5) Asian
Panel A. Age 62					
RD Estimate	–0.000964	0.0528	–0.00754	–0.00632	0.0535
	(0.00746)	(0.0468)	(0.0354)	(0.00871)	(0.0569)
Observations	13,251,731	790,695	989,732	9,725,661	467,617
Clusters	8.152e+06	347384	467032	5.312e+06	173764
Outcome mean	0.171	0.278	0.192	0.153	0.253
Panel B. Full Retirement					
RD Estimate	0.0129	–0.00981	0.0562	0.00699	0.0493
	(0.0115)	(0.0556)	(0.0472)	(0.0122)	(0.0732)
Observations	8,835,844	487,486	632,884	6,600,593	274,026
Clusters	3.621e+06	256494	263546	2.859e+06	122286
Outcome mean	0.169	0.271	0.186	0.153	0.244

Notes: This table presents regression discontinuity estimates of an indicator that a homeowner realizes a distressed home sale in a given year around retirement age. Panel A analyzes the discontinuity around age 62, while Panel B analyzes the discontinuity at full retirement age, which varies by birth year. Outcomes have been multiplied by 100 for legibility. Standard errors in parentheses. All specifications include fixed effects that interact county and purchase year.

$$y_{it} = \beta * 1[Eligible]_{it} + \gamma_i + \gamma_{age(i,t)} + \gamma_t + \varepsilon_{it}$$

That is, we regress an outcome on an indicator for eligibility, individual fixed effects, age fixed effects, and calendar month fixed effects. This design compares observationally similar homeowners who differ only in their eligibility for benefits, allowing us to distinguish the impacts of OASI eligibility from potentially confounding factors, such as eligibility for Medicare (Goldsmith-Pinkham et al. 2023). Table 11 presents estimates from this specification. We find that the estimated impacts of eligibility on the realization of both all sales and distressed sales is highly sensitive to controls. This is likely due to the identifying variation consisting of month-to-month variation in eligibility. Therefore, we conclude that this design yields limited insight into the impacts of eligibility on housing stability and distressed sales.

2.4 Discussion

The results presented in this section suggest that there is no evidence of a discontinuous change in economic well-being at age 62, when individuals become eligible for OASI bene-

Table 4: Discontinuity in Realized Returns Around Retirement

	(1) Pooled	(2) Hispanic	(3) Black	(4) White	(5) Asian
Panel A. Age 62					
RD Estimate	–0.0447	0.745	–0.994	–0.0438	–0.191
	(0.103)	(0.559)	(0.737)	(0.111)	(0.512)
Observations	119,855	5,683	3,678	91,210	3,515
Clusters	66786	2937	1667	50794	1913
Outcome mean	1.716	–0.0385	–1.801	2.029	0.198
Panel B. Full Retirement					
RD Estimate	0.101	0.136	–0.0918	0.112	–0.486
	(0.130)	(0.819)	(0.842)	(0.129)	(0.658)
Observations	85,642	3,602	2,183	66,030	2,071
Clusters	32774	1705	973	29155	1194
Outcome mean	1.846	0.202	–1.802	2.101	0.657

Notes: This table presents regression discontinuity estimates of realized annual housinsg returns among homeowners who sold their properties in a given year around retirement age. Panel A analyzes the discontinuity around age 62, while Panel B analyzes the discontinuity at full retirement age, which varies by birth year. Outcomes have been multiplied by 100 for legibility. Standard errors in parentheses. All specifications include fixed effects that interact county and purchase year.

fits. This finding suggests that the benefits of OASI, to the extent that they impact realized housing returns, displacement, and distressed sales, may accumulate gradually over time. In addition, this finding should be viewed in the context of declining total household earnings during retirement years. To illustrate this, Appendix Figure 3 plots household income by race/ethncity over the life cycle using a sample of homeowners in the Survey of Income and Program Participation. Total household income falls. To the extent that mortgage payments remain roughly constant throughout the term of the mortgage, this decline in income may represent a countervailing force that increases exposure to financial distress among retirement-age homeowners. Our results also reveal persistent racial and ethnic differences in economic well-being among OASI beneficiaries. The finding that these results persist beyond retirement age implies that OASI benefits are not sufficient in order to close these gaps. Motivated by this finding, the following section analyzes racial and ethnic differences in job loss during working years, as well as the contribution of those labor market disparities to disparities at retirement age.

3 Racial Differences in Exposure to Job Loss and Distressed Sales

This section analyzes racial/ethnic differences in job loss, as well as the contribution of those differences to disparities at retirement age. We use a second novel linked administrative dataset housed at the US Census. This dataset allows us to simultaneously observe job losses, home sales, realized returns, and homeowner race/ethnicity.

3.1 Data

In order to study racial differences in exposure to job loss and distressed sales, we leverage confidential microdata maintained by the US Census Bureau. These data contain highly accurate measures of individual job losses and incomes linked to property transaction records. This data set is built from five main input datasets.

The first dataset contains measures of annual earnings from tax records reported to the US Internal Revenue Service via forms 1040 (individual income tax) and 1099 (miscellaneous income). These data start in the year 2000 and cover the universe of US tax filings. These data are in a panel structure, allowing us to follow individuals over time, as well as to link individuals to dependents listed on tax returns. This latter feature of the data enables measurement of family relationships (i.e., identification of spouses and children).

The second dataset is the The Longitudinal Employer-Household Dynamics (LEHD) data (Vilhuber et al. 2018). The LEHD contains quarterly earnings and employment records sourced from state unemployment insurance tax filings. A key advantage of these data over the IRS data is that the LEHD was specifically designed to link employers to households, allowing us to analyze the role of firms in generating income volatility. For covered states and years, these data contain the universe of earnings and employment records covered by unemployment insurance.

The third dataset is the Census' Best Race File, which assigns individuals race/ethnicity based on self-reports from multiple sources (e.g., decennial censuses, American Community Survey, etc.). The Best Race File also includes granular distinctions within racial/ethnic categories (e.g., nationality or region within broad ethnic groups). The data we analyze includes the data used in Chetty et al. (2020) to compare labor market outcomes and intergenerational mobility by race and ethnicity.

The fourth dataset is comprised of administrative property transaction records assembled by Black Knight (also known as deeds records) that are held by the Census and include records of property sales. Transactions of property are required to be registered by local governments, which typically record the identities of the buyers and sellers, as well as the transaction price of the property. In Kermani and Wong (2021), we develop an algorithm for observing repeat sales of properties, which allows us to measure the annual returns realized by a given homeowner living in a given property.

The fifth dataset is confidential microdata from the American Community Survey (ACS). Although the preceding datasets offer a high degree of granularity for measuring demographic (e.g., race/ethnicity, age, sex) and labor market characteristics of individauls, they lack a number of additional features that may be relevant for determining racial/ethnic differences in retirement security. We leverage ACS microdata in years between 2005 and 2016. These datasets allow us to observe individual characteristics including education, occupation, industry, hours worked, and self-reported homeownership status.

These five datasets were linked at the individual level within the US Census. Table 5 provides summary statistics on the sample linked with the ACS. While many prior studies have analyzed each of these data sources in isolation, the linkage between the property records and the administrative income and employment data, as well as the ACS data, is novel and enables us to advance the study of how job losses during prime working years destroy housing wealth through distressed sales and lead to later financial disparities in retirement security.

Table 5: Summary Statistics

	Mean	SD	N
Age	44.97	9.621	5795000
Share Black	0.07716		5795000
Share Hispanic	0.1013		5795000
Share Female	0.451100		5795000
Year	2009	2.867	5795000
Quarterly Earnings	16710	47820	5795000
Any Displacement	0.06082		5795000
Any Mass Layoff	0.005441		5795000

Notes: This table presents summary statistics for the analysis sample using the merge with the American Community Survey. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY23-CES010-022.

3.2 Racial Differences in Exposure to Job Losses

To estimate racial differences in the liklihood of job loss by race and ethnicity, we turn to the LEHD data. This allows us to construct measures of quarterly job separations. We construct a panel of income and employment for a set of workers indexed by i over quarters indexed by t. We then estimate regressions of the following form:

$$1[separation]_{it} = \beta_0 1[Black_i] + \beta_h 1[Hispanic_i] + X'_{it}\gamma + \varepsilon_{it} \quad (1)$$

In the above, $1[separation]_{it}$ is an indicator that a homeowner i observed at t experiences

a separation. The explanatory variables are indicators that i is identified in the Best Race File as being non-Hispanic Black or Hispanic of any race. X_{it} denotes a vector of controls.

We analyze two measures of separations. The first measure is an indicator that a homeowner experiences any type of separation from their primary employer. As is standard practice in this literature, we exclude transitions that involve large groups of workers moving from one firm to another.[2] The second measure is an indicator that a homeowner experiences a separation that is part of a mass layoff. We apply a standard definition of mass layoffs, and define firms conducting mass layoffs as those that exhibit a loss of employment of 30 percent or more.

In order to maximally leverage the rich demographic information available on individuals in our study sample, we restrict attention to individuals who are observed in the ACS data, for whom we can observe characteristics like educational attainment and occupation. Accordingly, t indexes the quarter in which an individual was interviewed, and $1[separation]_{it}$ is an indicator that an individual experienced a separation in the 8 quarters following the interview. We restrict to full-time workers at the time of the interview, and require that a worker must have at least four quarters of tenure at their primary job.

We present results from estimating Equation 1 in Tables 6 and 7. We find that Black and Hispanic homeowners exhibit substantially higher rates of job instability relative to White homeowners. While about 5.8 percent of White homeowners experience a separation in the year following the ACS interview, this number is 1.2 percentage points and 0.6 percentage points higher for Black and Hispanic homeowners, respectively (Table 6, Column 1). Much of this difference can be explained by worker demographics. Including worker controls reduces the Black-White difference by about 38 percent, and flips the sign of the Hispanic-White difference. Including controlling for the identity of the firm (specifically, adding fixed effects that interact firm, county, and $1k bins of quarterly earnings) results in further reductions to the Black-White gap, from 0.71 percentage points to 0.16 percentage points. Similar patterns appear when analyzing racial/ethnic differences in exposure to mass layoffs (Table 7). For mass layoffs, firm effects explain an even larger share of the Black-White and Hispanic-White gaps.

Given that job separations entail substantial and persistent job losses, these results imply that racial/ethnic differences in job instability during working years have cumulating effects that exacerbate racial/ethnic differences in wealth at retirement. This is particularly the case given prior results indicating modest differences in savings rates by race (Kermani and Wong 2021). While these results indicate a direct channel through which disparities in working years can impact wealth disparities in retirement years (i.e., lower incomes lead to lower wealth), the following section analyzes an indirect channel, namely, whether higher levels of job instability among Black and Hispanic workers inhibit housing wealth accumulation.

[2]In the LEHD data, firms are identified by SEIN.

Table 6: Racial/Ethnic Differences in Exposure to Separations

Outcome	Any Separation (1)	Any Separation (2)	Any Separation (3)
Black	1.151	0.713	0.155
	(0.062)	(0.062)	(0.075)
Hispanic	0.571	–0.265	–0.587
	(0.057)	(0.059)	(0.076)
White Mean	5.834	5.834	5.834
Clusters	5,582,000	5,582,000	5,582,000
Controls	Basic	+ County, Age, Education, Earnings	+ Firm

Notes: This table presents estimates of racial/ethnic differences in exposure to job instability. The outcome is an indicator that a homeowner experiences a displacement in the four quarters following interview. Each column corresponds to a different set of controls. Column 1 presents results that include fixed effects that interact year and county. Column 2 adds three additional sets of fixed effects: interacting county, female, and 5-year age bins, interacting county and educational attainment, and interacting county and bins of quarterly earnings measured three quarters before the interview (bins of 1000 dollars). Column 3 adds fixed effects that interact firm, county, and the same income bins. Standard errors are clustered at the individual level. Data from sample of ACS respondents merged with employment histories described in Section 3.1. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY23-CES010-022.

3.3 Impacts of Job Loss on Distressed Sales

To analyze the impacts of job losses on distressed sales, we estimate event studies around job separations. In order to do so, we address three empirical challenges that arise from our environment. The first challenge entails measuring distressed sales. Because different local governments differ greatly in the legal requirements surrounding foreclosure proceedings, such events are not consistently coded across areas in the Black Knight data. Kermani and Wong (2021) show that foreclosures (and short sales) typically entail very negative returns. Therefore, we restrict attention to a sample of homeowners for whom we can observe the purchase price of their property. This allows us to compute an annualized return on that property for any subsequent sale. Our measure of foreclosures is any sale with a negative nominal rate of return, which we refer to as distressed sales.

A second challenge entails defining a control group for homeowners that experience a job loss. As noted by recent work on difference-in-difference estimators (e.g., Sun and Abraham 2021; De Chaisemartin and d'Haultfoeuille 2020), using the outcomes of early-treated units as a proxy for the potential outcomes of later-treated units creates bias in the presence of treatment effect heterogeneity. In order to circumvent these issues, for homeowner i who

Table 7: Racial/Ethnic Differences in Exposure to Mass Layoffs

Outcome	Any Mass Layoff (1)	Any Mass Layoff (2)	Any Mass Layoff (3)
Black	0.251	0.218	0.013
	(0.020)	(0.020)	(0.015)
Hispanic	0.255	0.164	0.031
	(0.019)	(0.020)	(0.016)
White Mean	0.497	0.497	0.497
Clusters	5,582,000	5,582,000	5,582,000
Controls	Basic	+ County, Age, Education, Earnings	+ Firm

Notes: This table presents estimates of racial/ethnic differences in exposure to job instability. The outcome is an indicator that a homeowner experiences a mass layoff in the four quarters following interview. Each column corresponds to a different set of controls. Column 1 presents results that include fixed effects that interact year and county. Column 2 adds three additional sets of fixed effects: interacting county, female, and 5-year age bins, interacting county and educational attainment, and interacting county and bins of quarterly earnings measured three quarters before the interview (bins of 1000 dollars). Column 3 adds fixed effects that interact firm, county, and the same income bins. Standard errors are clustered at the individual level. Data from sample of ACS respondents merged with employment histories described in Section 3.1. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY23-CES010-022.

buys their homeowner in q_0 and separates in quarter $q_1 > q_0$, we form a control group that is comprised of homeowners who purchased their home in q_0 i but who did not separate from their job in q_1. We then estimate event studies of the following form:

$$y_{it} = \alpha_i + \gamma_{s(t),g(i)} + \sum_k \beta_k 1[t = k + s(i)]1[separated]_i + \varepsilon_{it} \tag{2}$$

In Equation 2, y_{it} denotes an outcome of interest for individual i in quarter t. $1[separated]$ is an indicator that an individual separates in quarter $s(i)$ (and is 0 if the individual is part of the aforementioned control group). β_k represents the event study coefficients of interest, capturing the impact of a separation on outcomes k quarters after the separation. Note that this approach applies a set of event time fixed effects $\gamma_{s(t)}$, rather than calendar time fixed effects (i.e., γ_t). This approach circumvents the aforementioned identification issues. Intuitively, Equation 2 does not use already-treated units as controls for not-yet-treated units. Instead, it treats each set of households within each cell $g(i)$ as experiencing a (potential) separation in the same month (i.e., $s = 0$). In Equation 2, the $g(i)$ cells represent groups that are interacted with the event time fixed effects.

A third econometric challenge is constructing a plausibly exogenous measure of job losses. Job separations are determined both by the actions of firms and of workers, raising the possibility that some of the observed patterns reflect not just the causal impacts of job loss, but also the endogenous decisions of workers to leave their jobs. To bring our analysis closer to the experimental ideal of randomly assigned job losses, we restrict our attention to workers with tenures of more than four years. The data prepared for the present analysis will support a planned subsequent analysis in our second year of work, which uses a quasi-experimental mass layoffs design to derive improved causal estimates of the impacts of job losses on distressed sales (as in Jacobson et al. 1993 and Sullivan and Von Wachter 2009).

We present results from estimating Equation 2 in Figure 2, which presents estimates separately by race/ethnicity, and for both any sale and any distressed sale (i.e., a sale with a negative return). White homeowners, for whom we have the largest sample size, exhibit a meaningful increase in home sales following a job separation. The increase largely subsides after 6 months, with more persistent impacts for any sales relative to distressed sales. At its peak, the annual distressed sale rate rises by 0.2 percentage points, on a base of about 0.17 percentage points, implying a substantial increase.

Impacts of separations for Black and Hispanic homeowners are less precisely estimated. While point estimates for Black and Hispanic homeowners are substantially larger than White homeowners (especially after 6 quarters following the separation), the confidence intervals overlap with both no effects and the relatively smaller effects exhibited by Hispanic homeowners.

In order to minimize noise, we estimate a pooled specification that collapses down to two time periods (i.e., pre- and post- separation). We define outcomes that are an indicator for any sale and any distressed sale within the time period. Table 8 and 9 present results from this specification, and yield a substantial improvement in precision. In particular, we find that separations increase distressed sales by 0.34 percentage points for White homeowners, 0.80 percentage points for Black homeowners, and 0.60 percentage points for Hispanic homeowners. These findings imply that Black and Hispanic homeownership is much more sensitive to job separations than White homeownership. These findings are consistent with those in Kermani and Wong (2021), who find that minority homeowners have much lower levels of liquidity than White homeowners.

These results should be interpreted in light of a number of limitations to our analysis. First, our analysis focused on a randomly-chosen set of 8 states. While the random selection of states suggests that these findings are likely representative, a prospective second year of work will use improved versions of the Black Knight data to expand the analysis nationwide. Second, the current version of the Black Knight data likely undercounts property sales. For example, annual sale rates in this sample are on the order of 1 percent (Figure 2). This figure is substantially smaller than the annual sale rates of about 4 percent observed in other settings (Kermani and Wong 2021). Our second year of work will make use of a refined algorithm for identifying property sales. This algorithm is actively being developed and was not yet available at the time of our analysis.

Table 8: Impact of Separations on Property Sales

Outcome	Any Sale (1)	Any Sale (2)	Any Sale (3)
$Post \times 1\{separated\}$	1.310	0.884	1.739
	(0.142)	(0.454)	(0.637)
Race/Ethnicity	White	Black	Hispanic
Outcome Mean	3.196	2.620	4.074
Clusters	112,000	8,800	7,300

Notes: This table presents differences-in-differences estimates of the impact of a separation. The outcome is an indicator that a homeowner sells their property. Regressions are estimated separately by race and ethnicity. Standard errors are clustered at the individual level. Data from sample of property records merged with employment histories described in Section 3.1. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY23-CES010-022.

3.4 Contribution to Household Wealth at Retirement

We combine the preceding analyses to estimate average household wealth at retirement for each racial/ethnic group under a counterfactual in which each racial/ethnic group experiences the same incidence and impacts of job losses as non-Hispanic White households, holding levels of income constant. This counterfactual serves to quantify the contribution of racial differences in unemployment risk to racial differences in wealth at retirement through the wealth-destroying effects of foreclosures.

Let the average financial rate of return to homeownership for race r be given by:

$$R_r = \pi_{r,Reg} R_{r,Reg} + (1 - \pi_{r,Reg}) R_{r,distress}$$

In the above, $\pi_{r,Reg}$ denotes the probability of a regular sale for a homeowner of race r, $R_{r,reg}$ is the average return for race r conditional on a regular sale, and $R_{r,distress}$ is the average return conditional on a distressed sale. Assume that job losses only affect returns by whether a homeowner realizes a regular sale or distressed sale. The difference in returns for race r between counterfactual returns and acual returns is given by $\Delta R_r = \Delta\pi_{r,Reg}(R_{r,Reg} - R_{r,distress})$, where $\Delta\pi$ denotes the counterfactual change in the probability of a regular sale. This object can be expressed as:

$$\Delta\pi_{B,Reg} = (\eta_B q_B - \eta_W q_W) \times C$$

In the above, q_r denotes the probability of job loss for a homeowner of race r, and η_r equals $\frac{\partial \pi_{r,reg}}{\partial q_r}$ is the reduced-form impact of job loss on the probability of a distressed sale. C denotes

Table 9: Impact of Separations on Distressed Sales

Outcome	Any Distressed Sale (1)	Any Distressed Sale (2)	Any Distressed Sale (3)
$Post \times 1\{separated\}$	0.336	0.798	0.601
	(0.062)	(0.257)	(0.295)
Race/Ethnicity	White	Black	Hispanic
Outcome Mean	0.629	0.899	0.793
Clusters	112,000	8,800	7,300

Notes: This table presents differences-in-differences estimates of the impact of a separation. The outcome is an indicator that a homeowner sells their property for less than the purchase price, which we use to define distressed sales. Regressions are estimated separately by race and ethnicity. Standard errors are clustered at the individual level. Data from sample of property records merged with employment histories described in Section 3.1. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY23-CES010-022.

a scaling factor that maps our reduced-form estimates to be comparable to annual returns. To compute this scaling factor, we can begin by calculating the counterfactual percentage change in distress. From Table 6 and Table 9:

$$\begin{aligned}\eta_B q_B - \eta_W q_W &= 0.00798 \times (0.0151 + 0.05834) - 0.00336 \times 0.05834 \\ &= 3.9003 \text{ basis points}\end{aligned}$$

As a percent of the Black-White difference in distressed sales (Table 9), this difference amounts to $\frac{3.9bp}{27bp} = 14.4$ percent. As reported in Kermani and Wong (2021), Table 2, the Black-White gap in distressed sales is $23.9 - 12.4 = 11.4$ percentage points. Therefore, we calculate that $\Delta\pi_{B,reg} = 11.4\% \times 14.4\% = 1.65\%$. Note that the implicit scaling factor C in this approach assumes that the proportional difference in distressed sale probabilities in our preferred measure of distressed sales can be mapped to the more accurately categorized distressed sales in Kermani and Wong (2021).

From Kermani and Wong (2021) (Figure A5), we have that the difference in annual returns between regular and distressed sales is about 5.413 percentage points for White homeowners and 6.427 percentage points for Black homeowners. Therefore, we estimate that $\Delta R_B = 6.427 \times 1.65 = 10.6$ basis points. Given an externally-estimated Black-White gap of about 1.8 percentage points (Kermani and Wong 2021), this represents only about 6 percent of the overall gap.

To cumulate the impacts of returns on homeowners in retirement, we follow the accounting framework developed in Kermani and Wong (2021). Specifically, we compute average wealth

held in the primary home at retirement age by a household of race $r \in \{Black, White\}$ using the following equation:

$$\hat{H}_{r,65} = \sum_{s \in \{cash, mort\}} \sum_{t=25}^{65} \left(p_{r,s,t} \times H_{r,s,t} \times R_{r,s}^{(65-t)} \right) \tag{3}$$

In the above, $p_{r,s,t}$ denotes the unconditional probability of becoming a first-time home buyer at age t for race r, in a purchase of type s (mortgaged or cash). $H_{r,s,t}$ denotes the average house value at first-time home purchase, and $R_{r,s}$ denotes the average annual return on a home purchased by a homeowner of race r of purchase type s.

This formulation computes average primary housing wealth at retirement by inflating the value of households' first home at purchase at each age using mean housing returns for each race and purchase type. We do not explicitly model transitions out of homeownership through distressed sales, which are captured in the race-specific returns $R_{r,mort}$. All computations follow those using the PSID described in Kermani and Wong (2021).

Unsurprisingly given our relatively modest counterfactual differences, we find that a counterfactual in which Black homeowners realize similar rates of job loss and similar impacts of job loss on distressed sales as white homeowners only explains about 1.1 percent of the Black-White diffeerence in primary housing wealth at retirement of $169,389 measured in the PSID. This amount is also small relative to plausible magnitudes of the direct impact of earnings losses on wealth accumulation. Von Wachter et al. (2009) estimate earnings losses between $110,000 to $140,000 in present discounted value terms, estimated using earnings losses from mass layoffs in the 1982 recession.

However, concluding that differences in job stability do not meaningfully contribute to observed gaps in housing wealth would be premature for two reasons. First, we again emphasize the limitations of the data (discussed in Section 3.1). Analysis conducted in our second year of work will likely lead to revised estimates. Second, our measure of job separations is subject to concerns about endogeneity in the separations decision. During our second year of work, we will extend our results to look at separations that occur as part of a mass layoff.

4 Discussion and Conclusion

This report summarizes the first year of work analyzing racial differences in housing-related measures of economic well-being among OASI beneficiaries. We constructed two novel administrative datasets. The first, housed at the Fisher Center at UC Berkeley, used voter registration records and property records to analyze patterns of displacement, foreclosure, and realized housing returns among OASI beneficiaries. Analysis of this data revealed that racial differences persist throughout retirement age. Moreover, there is no evidence of a discontinuous change in outcomes when homeowners become eligible for OASI benefits.

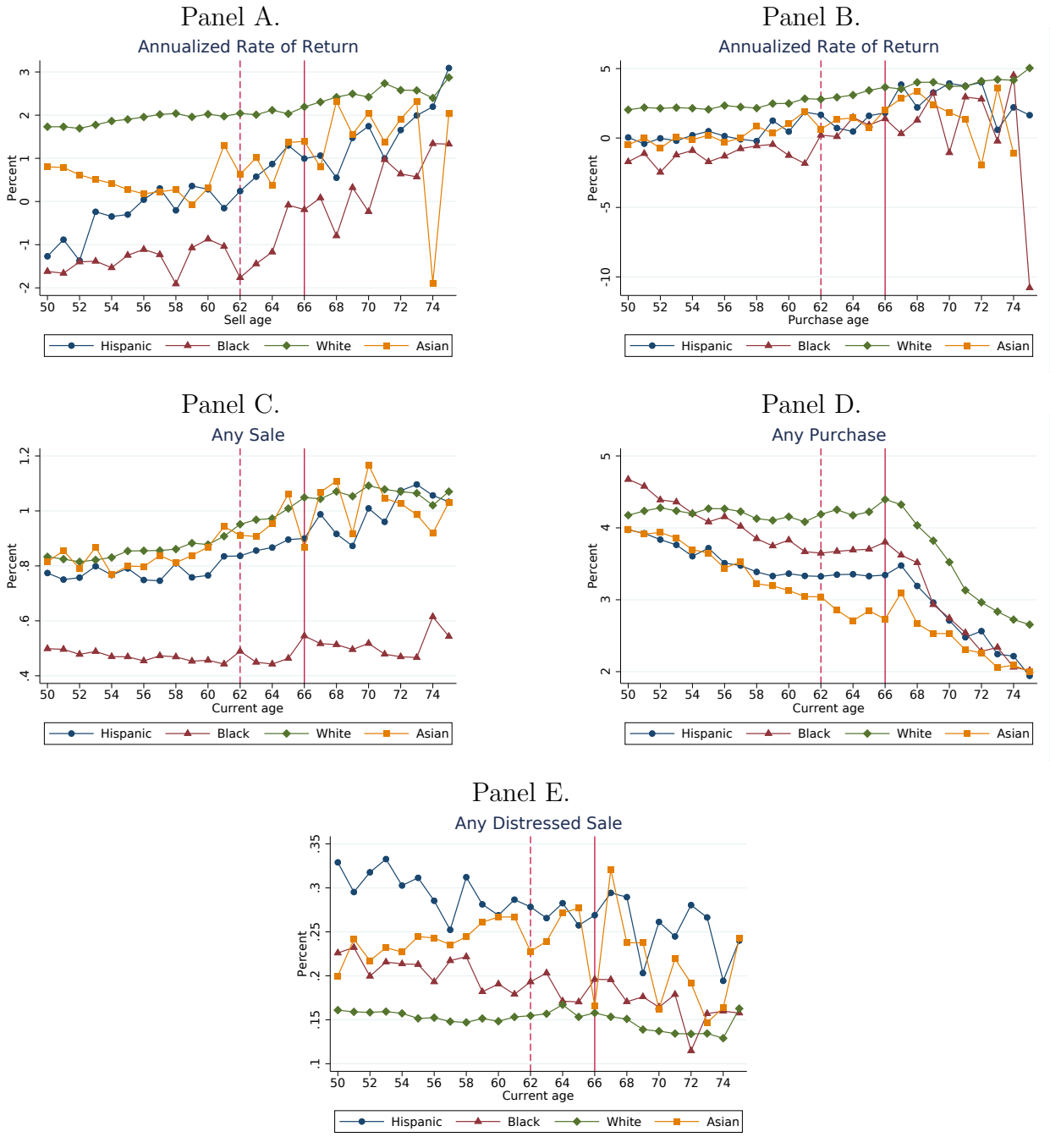
The second novel administrative dataset, housed at the US Census Bureau, combined data on earnings and employment from tax and unemployment insurance records. Our initial

results indicate that the impacts of job loss may be more severe for minority homeowners, and result in larger increases in distressed sales following a job loss. While this first year of work yielded novel results, our analyses of the impact of job losses was limited by the likely presence of bias in the causal estimates arising from the endogeneity of job separations. Having assembled the necessary data, in future work, we will advance this research agenda by conducting a quasi-experimental mass layoff analysis. The mass layoff analysis will yield improved estimates of the casual impact of job loss on foreclosure and realized returns, which in turn will yield a more accurate accounting of the impact of racial/ethnic disparities during working years on disparities at retirement age.

Our analysis yields two policy implications. First, our first set of results using the Fisher Center data revealed no meaningful changes in patterns of housing wealth accumulation or housing instability at retirement age. This finding implies reduced scope for social safety net programs that become available at retirement likely to reduce racial and ethnic disparities in overall wealth during retirement years. From a policy perspective, this suggests scope for means-tested policies to target low-wealth households. For example, one possibility is to expand the use of asset-based tests (e.g., those used for Medicaid eligibility) to target programs that seek to address disparities arising from wealth inequality at retirement.

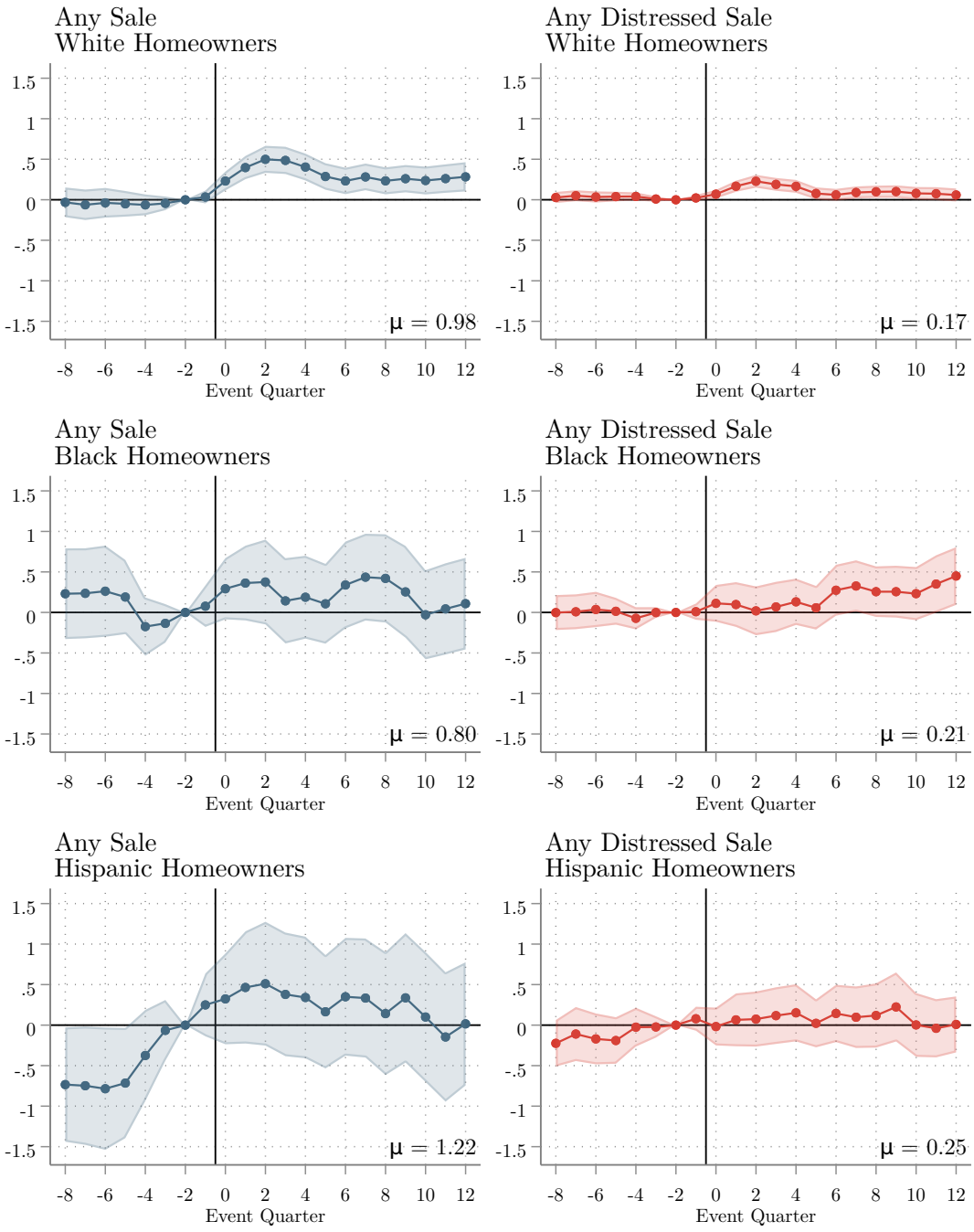
A second policy implication is that the racial/ethnic disparities in wealth at retirement age are a direct result of racial/ethnic disparities in labor market experiences during working years. An underappreciated aspect of these disparities during working years is job instability (Kermani and Wong 2021). This fact suggests that interventions that reduce income and employment instability for minorities is likely to positively support long-term wealth accumulation. Thus, expanding policies such as unemployment insurance are likely to reduce gaps both during working years and at retirement.

Figure 1: Racial/Ethnic Differences in Economic Security



Notes: This figure presents five binned scatterplots of measures of economic well-being separately by race and ethnicity across the age distribution. The outcome in Panel A is the annual unlevered rate of return realized, plotted at the age at which the homeowner sold the home. The outcome in panel B is the annual unlevered return plotted at the age at which the homeowner purchased the home. The outcome in Panel C is an indicator that a homeowner sold a home at a given age. The outcome in Panel D is an indicator that a homeowner purchased a new home. The outcome in Panel E is an indicator that a homeowner sold their home in a distressed sale (and includes short sales). Each figure plots series separately for Hispanic, Black, White, and Asian homeowners. Results reveal no evidence of a discontinuity in trends around retirement age (e.g., age 62 or 66).

Figure 2: Impacts of Job Loss on Property Sales by Race/Ethnicity



Notes: This figure depicts the quarterly time path of outcomes around a job separation that occurs at event time $t = 0$. The outcomes are an indicator that a homeowner has sold their property in the last four quarters (*Any Sale*) and an indicator that a homeowner has sold their property in the last four quarters for less than the original purchase price (*Any Distressed Sale*). Samples are split by race and ethnicity. Data from sample of property records merged with employment histories described in Section 3.1. All results were approved for release by the US Census Bureau, authorization number CBDRB-FY23-CES010-022.

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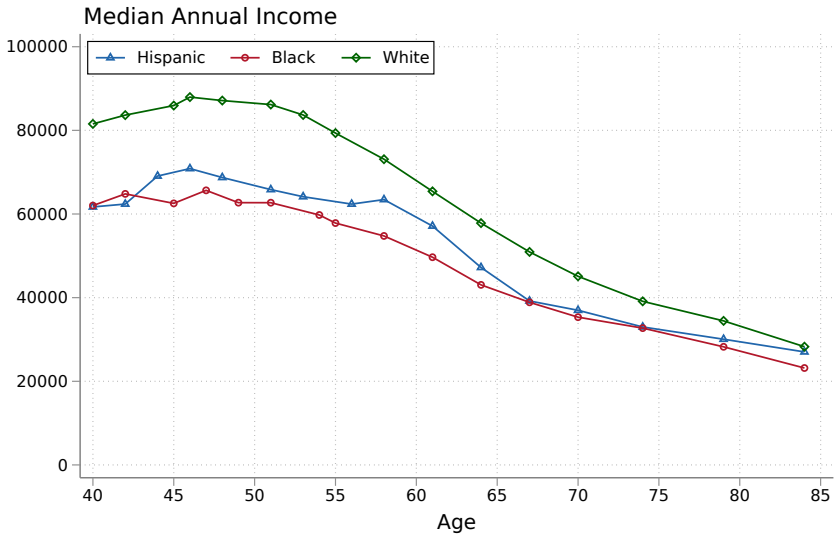
Appendix

Figure 3: Household Income Over The Life Cycle



Notes: This figure depicts total household income by race and ethnicity by age for a sample of homeowners in the Survey of Income and Program Participation. Sample includes survey waves between 1992 and 2017 and applies survey weights. Age refers to the age of the reference homeowner. Figure shows a gradual decline in income throughout retirement age for Black, White, and Hispanic homeowners.

Table 10: Heterogeneity in Discontinuity in Any Sale

Heterogeneity	Income Low	Income High	CLTV Low	CLTV High	DTI Low	DTI High
Panel A. Age 62						
RD Estimate	0.0259	0.0686*	0.0876*	0.103**	0.343***	0.00611
	(0.0259)	(0.0383)	(0.0511)	(0.0490)	(0.0732)	(0.0601)
Observations	6,411,636	6,532,781	4,080,749	4,081,123	1,450,382	1,497,528
Clusters	3.102e+06	2.038e+06	1.203e+06	1.987e+06	615305	781942
Outcome Mean	0.723	1.054	1.215	1.273	1.024	1.004
Panel B. Full						
RD Estimate	0.113***	–0.0173	0.0317	0.00284	0.117	0.0937
	(0.0416)	(0.0373)	(0.0655)	(0.0642)	(0.0819)	(0.0752)
Observations	4,219,394	4,404,501	2,041,519	2,041,857	937,075	985,830
Clusters	1.418e+06	2.311e+06	1.017e+06	994382	505832	550724
Outcome Mean	0.784	1.125	1.301	1.446	1.098	1.081

Notes: This table presents regression discontinuity estimates of an indicator that a homeowner sells their property in a given year around retirement age. Panel A analyzes the discontinuity around age 62, while Panel B analyzes the discontinuity at full retirement age, which varies by birth year. Columns correspond to different dimensions of heterogeneity. Outcomes have been multiplied by 100 for legibility. Standard errors in parentheses. All specifications include fixed effects that interact county and purchase year.

Table 11: Difference-in-Differences Estimates

	(1)	(2)	(3)	(4)
Panel A. Any Sale				
1[Eligible]	0.0414***	0.000125	–0.00354*	–0.00228
	(0.000396)	(0.000453)	(0.00203)	(0.00211)
Outcome Mean	0.0458	0.0526	0.0533	0.0530
Panel B. Any Distressed Sale				
1[Eligible]	0.00179***	–0.00251***	0.00188***	0.00198***
	(0.000166)	(0.000196)	(0.000648)	(0.000689)
Outcome Mean	0.0118	0.0125	0.0118	0.0117
Observations	341,385,912	341,385,912	341,385,912	341,385,912
Clusters	1.355e+06	1.355e+06	1.355e+06	1.355e+06
Time FE		Y	Y	Y
Age FE			Y	Y
Individual FE				Y

Notes: This table presents differences-in-differences estimates of the impact of eligibility for full retirement benefits. The outcome in Panel A is an indicator that a homeowner sells their property in a given month. The outcome in Panel B is an indicator that a homeowner realizes a distressed home sale in a given month. Both outcomes have been multiplied by 100 for legibility. Standard errors clustered at the individual level in parentheses.

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