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Dynamic Racial Wealth Inequality Accounting, 1860 – 2020[†]

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Abstract

Post-Emancipation hopes for Black–White wealth convergence in the U.S. quickly soured with the rise of Jim Crow, and seem elusive today. We investigate what frictions account for racial wealth inequality dynamics since 1860. Guided by the history of racial exclusions in both capital and labor markets, we introduce group-specific wealth accumulation frictions along with group-specific labor market earnings in a parsimonious workhorse incomplete markets model. We calibrate the path of these model-based frictions to match wealth distribution dynamics by race from 1860 to 2020. Compared with White households, Black households not only earn less but also face larger wealth downside risks through the lens of the model. Financial frictions appear essential for rationalizing the left tail of wealth, especially the larger share of zero wealth Black households. Around the Civil Rights era, calibrated racial wealth destruction risk gaps spiked and blunted racial wealth convergence stemming from historic Black earnings gains. By 2020, the wealth destruction risk gap is about 5 percentage points larger for Black households. A wedge-based accounting reveals a sizable contribution of financial downside risks to racial wealth inequality. Finally, we present plausible evidence on racial wealth downside risk gaps. We conclude that models with wealth fragility frictions are a promising direction for the study of racial wealth disparities.

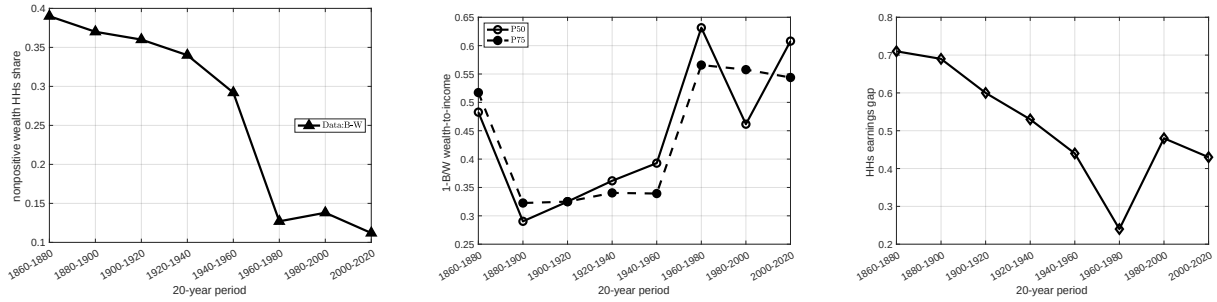
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1 Introduction

America's Black-White wealth inequality remains large: since 1980, Black households' average wealth has plateaued slightly below one fifth of White households' average wealth (Derenoncourt et al., 2024). In comparison, earnings have converged more since Emancipation: Black households' average earnings reached almost three quarters of White households' average earnings at the height of the Civil Rights era, but retreated somewhat since (Bayer and Charles, 2018; Kondo et al., 2024). In this paper, we ask how financial channels along with earnings account for racial wealth inequality dynamics since 1860.

Figure 1: Selected Components Shaping Mean Black-White Wealth Differences



(a) Zero wealth share gap (b) Relative wealth-to-income (c) Relative earnings

Note: Wealth-to-income ratios use group-specific average household earnings. Wealth percentiles are among positive wealth households. The relative gap is 1 minus the Black/White ratio. Source: Authors' calculations using Derenoncourt et al. (2023, 2024).

To frame our approach, let us rewrite relative Black-White mean wealth in Equation 1 below

$$\underbrace{\frac{\bar{a}_B}{\bar{a}_W}}_{\frac{\text{Black}}{\text{White}}\text{ mean wealth}} = \underbrace{\frac{\Pr\left[a_B^i > 0\right]}{\Pr\left[a_W^i > 0\right]}}_{\frac{\text{Black}}{\text{White}}\text{ positive wealth share}} \times \underbrace{\frac{\bar{a}_{B|a>0}/\bar{y}_B}{\bar{a}_{W|a>0}/\bar{y}_W}}_{\frac{\text{Black}}{\text{White}}\text{ positive wealth-to-income}} \times \underbrace{\frac{\bar{y}_B}{\bar{y}_W}}_{\frac{\text{Black}}{\text{White}}\text{ mean income}}, \tag{1}$$

where $\bar{\cdot}$ is the mean operator and nonpositive wealth is zero following Derenoncourt et al. (2024). Equation 1 recasts racial wealth gaps as racial differences in (a) the share of zero wealth households, (b) wealth-to-income ratios, and (c) incomes. Beyond racial differences in earnings, differences along positive wealth extensive and intensive margins also matter. In fact, Figure 1 suggests all three margins have been distinctly active since 1860.[1] We argue that racial gaps in both earnings and wealth downside risks are crucial for understanding the joint evolution of these facets of American racial wealth inequality.[2]

[1] See Figure A1 in the appendix for mean wealth inequality dynamics as opposed to the Black-White ratio for median wealth and for the 75th wealth percentile shown in Figure 1.

[2] See Albright et al. (2021); Logan (2023); Humphries et al. (2025); Bayer et al. (2017); Kermani and Wong (2024) for past or contemporaneous events (anti-Black violence, incarceration, housing sales) that disproportionately reduce Black wealth.

Why Downside Risks as Financial Frictions? Albright et al. (2021) trace striking and persistent effects of the 1921 Tulsa Race Massacre and other anti-Black violence events during the Red Summer of 1919: not only did the Greenwood "Black Wall Street" and other directly targeted neighborhoods burn, but homeownership and white-collar occupation attainment were also persistently lower in these areas as well as the communities connected to Tulsa by kin. Our modeling paradigm reflects this historical reality of exclusions and oppression against Black-owned assets under Jim Crow.[3]

The contemporary environment too *may* feature more downside risks for Black-owned wealth *compared with that of White households*. For example, Kermani and Wong (2024) document the greater incidence of fire sales and thereby lower housing returns from distressed sales for Black and Hispanic households, relative to White households. Humphries et al. (2025) also point to a significant link between rising Black incarceration rates and downside risks to homeownership.[4]

We turn to downside financial risks to capture multifaceted channels that shape wealth dynamics along with earnings differences. The key idea behind our financial fragility wedge is the possibility of more significant downside risks for Black households. As is consistent with the history of racism in America, we modify the benchmark model of Aiyagari (1994) to include a wealth destruction or expropriation risk that may affect Black and White households differently.

Our Approach Specifically, we study the drivers of racial wealth differences through the lens of a parsimonious incomplete markets model with both labor income inequality and wealth accumulation frictions that is calibrated to match wealth distribution dynamics by group–including the left tail of the wealth distribution. Needless to say, frictions to wealth accumulation shape both the extensive margin of wealth (*zero wealth* households) and the intensive margin of wealth accumulated relative to income, while the racial differences in incomes too endogenously shape racial gaps along both margins.

In the spirit of Chari, Kehoe and McGrattan (2007), we recover the model-based group-specific, time-varying, financial wedges needed, *in conjunction with* racial labor income differences, to account

[3] Kahrl (2024) documents the "Black wealth tax"under Jim Crow, systemic burdens and pervasive risks placed on Black wealth. For more on the Red Summer, see Brockell (2021) and McWhirter (2011). Logan (2023) also shows Black politicians in counties that mobilized more local tax revenues during Reconstruction faced more anti-Black violence.

[4] Examples of indirect shocks to Black wealth include the disparate destruction of Black urban centers during the U.S. interstate highway system expansion (see Valenzuela-Casasempere, 2024), redlining policies (see Aaronson, Hartley and Mazumder, 2021), or the collapse of the Freedman's Savings Bank (see Célérier and Tak, 2025; Edwards, 2024; Bogan et al., 2025). Taylor (2019) also argues that redlining morphed into federally-stamped "predatory inclusion" of Black homebuyers in the 1970s even as suburban homeownership grew among White households.

for bi-decadal racial wealth dynamics from 1860 to 2020. We then develop an accounting method of these frictions' respective contributions to the racial wealth gaps' decomposition in Equation 1. Finally, using existing findings and new empirical evidence, we explore the plausibility of the significant racial gaps in wealth accumulation downside risks that we recover.

Key Findings. While racial gaps in labor market determinants (see Figure 1, panel c) have been extensively researched, less systematic attention has been *jointly* paid to sizable racial wealth differences at both the intensive margin (see Figure 1, panel b) and the extensive margin (see Figure 1, panel a). Yet, the extensive and intensive margins do not appear to have trivial historical co-movement patterns with each other or with racial earnings gaps. Racial gaps in the share of zero wealth households declined but remained large until 1940, sharply fell between 1940 and 1980, and have stagnated since. The intensive margins gaps tell a different story: a quick significant convergence by 1900, a modest widening between 1900 and 1960, followed by a large sharp divergence.

We find that, in addition to racial labor market gaps, a financial friction akin to greater downside risk to wealth for Black households is essential for understanding the evolution of differences in wealth between Black and White households, especially at the left tail. In the early 1900s, the downside risk wedge fell substantially, helping drive down the Black-White gap in "zero wealth" households. Around the Civil Rights era, the downside risk gap opened up significantly as the racial labor income gap shrunk, before resuming its downward march. In the last two decades of our analysis (2000–20), the Black-White gap in downside risk remains substantial, at nearly 5 percentage points. Our simulations indicate that racial wealth convergence depends crucially on the closing of both labor market and financial frictions.

Related Literature. While there is a large empirical literature on ongoing historical and persistent wealth disparities between Black and White households in the U.S., far fewer contributions to the quantitative macroeconomics literature evaluate these differences. From both a modeling and an empirical perspective, a key contribution of our work is to inform the types of models and evidence that are important for the study of racial wealth dynamics: racial differences in downside financial risks are crucial.

In an incomplete-markets, heterogeneous-agents Bewley-Imrohoroglu-Huggett-Aiyagari model, we estimate the time-varying frictions needed to rationalize moments of the wealth distributions by group over time, especially novel evidence on zero-wealth households. Our wedge-based accounting also

bridges studies decomposing wealth inequality and the significant racial gap in the mass of zero wealth households highlighted in Derenoncourt et al. (2023) and Oliver and Shapiro (1989, 1990).

By highlighting the crucial role of the path of downside financial risks since 1860, we contribute to the burgeoning quantitative literature on racial wealth inequality, including Ashman and Neumuller (2020); Aliprantis, Carroll and Young (2022); Albuquerque and Ifergane (2023); Boerma and Karabarbounis (2023); Nakajima (2023); Athreya et al. (2025).[5]

Our work also relates to ongoing empirical research on the factors that differently shape Black and White fortunes in America, especially Andrews et al. (2017); Choukhmane et al. (2023); Albright et al. (2021); Argyle et al. (2025); Avenancio-León and Howard (2022); Bogan et al. (2025).[6]

Our paper is structured as follows. In Section 2, we introduce our benchmark model and the types of frictions we seek to identify from the data. In Section 3, we present our quantitative approach and findings. We examine alternative model configurations in Section 4 to shed light on the mechanisms identifying key frictions and their robustness. In Section 5, we measure the dynamic contribution of each friction to racial wealth differences from 1860 to 2020. Finally, we present new suggestive evidence on racial differences in housing wealth downside risks in Section 6. Section 7 concludes our paper.

2 Model with Frictions in Labor and Asset Markets

2.1 Overview

We consider an economy populated by households labeled B for "Black" or W for "White."[7] We choose to have common preferences across households and attribute differences across groups to group-specific frictions in labor or financial markets. Instead of assuming permanent hierarchical racial differences in behavioral drivers such as the time discount rate or risk aversion, we uncover structural differences in

[5] De Nardi and Fella (2017) provide a review of quantitative models of wealth inequality and the channels typically incorporated to modulate wealth inequality. The downside risk we introduce is similar to exogenous heterogeneous returns rationalizing top wealth inequality – e.g., in Hubmer, Krusell and Smith (2020) and Benhabib, Cui and Miao (2024). See also Falcettoni and Nygaard (2023) and Brouillette, Jones and Klenow (2021) on racial gaps in well-being.

[6] See also studies of racial capitalism defined by Jenkins and Leroy (2021) as "the process by which the key dynamics of capitalism ... become articulated through race". See also Darity, Hamilton and Stewart (2015) on stratification economics.

[7] Our approach could be applied to other groups to the extent that the data are available. Native Americans certainly experienced significant wealth loss and destruction. Feir, Jones and Redish (2024) document the dramatic reversal of fortunes for Native Americans. See Gordon Nembhard and Chiteji (2006) for a collection contrasting wealth distributions across various U.S. communities.

the environment and constraints across groups. In doing so, we deliberately shift away from a problematic view of racial inequality.[8]

Group-Specific Frictions. Therefore, the notion of "race" captured by the labels B and W in the model is one of systemic, group-based exclusions or privileges, which in turn shape individual decisions and cross-group disparities.[9] Group-specific frictions shape earnings and wealth accumulation, and may capture institutional group-based privilege or prejudice. Specifically, the model includes three types of wedges or group-based distortions to labor earnings and asset payoffs: (i) Black and White workers may earn different amounts per efficient unit of labor supplied, (ii) the asset return may differ across groups, and (iii) the downside risk of the asset may also differ across groups. These modeling choices are driven by two main considerations.

First, the existing literature emphasizes the income channel and the heterogeneous-returns channel as key drivers of racial wealth differences. For instance, Derenoncourt et al. (2024) distinguish three episodes in the evolution of the racial wealth differences: an income-driven episode (1870–1950), a savings-driven episode (1950–1980), and a returns-amplified episode (1980–2020). We relax some limitations in this conceptual framework: savings rates are exogenous, savings choices are independent of returns, and the decomposition does not flexibly identify multiple joint drivers of wealth inequality.

Second, the historical record points to systematic exclusion and discrimination in capital markets, from redlining and insurance underwriting barriers to outright expropriation risk. Kahrl (2024) and Flitter (2022) provide excellent historical and contemporaneous accounts of the differential treatment of Black wealth in America, while recent contributions like Kermani and Wong (2024) estimate a significant downside in realized housing returns for Black and Hispanic homeowners.[10]

[8] Peart and Levy (2003) question the use of behavioral differences across races of people as a foundation of economic heterogeneity, an approach they taxonomize as "parametric racism." They note that leading economists–especially Irving Fisher, who, in 1922, became the first president of the American Eugenics Society–made the troubling recommendation that some races and immigrant groups were "dysgenic": he thought they were inferior, less patient, lacking of foresight, and requiring to be bred out (Fisher, 1921).

[9] See Spriggs (2020) for an excellent discussion on the different approaches and issues inherent to modeling "race" as a social construct in economic models and empirical analyses. Our approach addresses aspects of the Spriggs critique: we allow group-specific frictions in all markets in our economy (labor markets and financial markets), instead of restricting them to only parts of the economy.

[10] Bogan et al. (2025) offer novel evidence on long-run generational trauma associated with the Freedman's Savings Bank failure. Giedeman (2011) contrasts the collapse of the Freedman's Savings Bank in 1874 with the federal bailout of Fannie Mae and Freddie Mac during the financial crisis of 2007–09. Myers (1995) and Ards and Myers (2001) also challenge the notion that racial differences in credit risk explain racial differences in access to capital.

Environment. For clarity, we present the baseline model without time-varying parameters. Later, in the calibration section, we estimate time-varying model parameters. Time is discrete, and the economy is populated by a mass m_j of households of group $j = \text{B, W}$. Given our partial equilibrium setup, one can think of these two groups as living in two parallel islands or economies that operate under similar or related model parameters.

Households are risk-averse and self-insure using borrowing and savings to smooth their consumption. Each household i derives a flow utility $u(c_{it})$ from consumption c_{it} at time t and has a discount factor β.[11] We assume each household inelastically supplies ℓ units of labor. Their labor earnings are subject to i.i.d. uninsurable labor productivity shocks $z \in \mathcal{Z}$ following a Markov process with a transition probability matrix $G(z'|z)$. Households borrow or save using an asset with risky payoffs to insure against income shocks and smooth consumption. The model is a partial equilibrium environment: the wage rate w per efficient unit of labor and the interest rate r are exogenously set.

Earnings Wedge. The earnings friction is captured by the wedge $\omega_{j,\ell}$, such that take-home earnings are given by $(1-\omega_{j,\ell})wz\ell$ for a j-household supplying $z\ell$ effective units of labor. For instance, if $\omega_{W,\ell} = 0$ and $\mathbb{E}[z]\ell = 1$, then Black workers' mean earnings are $(1 - \omega_{B,\ell})w$, while White workers receive w. The labor market wedge captures cross-group differences in earnings, including compositional differences in terms of education, industry, occupation, tasks, tenure, or employment rate.[12]

Excess Return Wedge. The wealth distribution in the U.S. is significantly right-skewed, as demonstrated by Saez and Zucman (2016). To partly account for the dynamics of within-group wealth inequality, we allow wealthier households to benefit from higher returns in our economy. This approach is consistent with recent evidence in Hubmer, Krusell and Smith (2020). We assume that a household with wealth $a > \overline{a}_j$ enjoys an excess return $\omega_{j,r}r$, on top of the baseline return r. To be precise, the normal one-period

[11] We adopt a dynastic perspective and also abstract from differences in survival probability across groups for parsimony. This setup makes it easier to contrast our results and the conceptual framework used to decompose historical racial wealth disparities in Derenoncourt et al. (2024). In an non-dynastic model, death risk itself may be due to racialized policies and treatment–e.g., lynchings (see Wells-Barnett, 2002), fatal police encounters (see GBD 2019 Police Violence U.S. Subnational Collaborators, 2021), or maternal morbidity (see Singh, 2020). See Blundell et al. (2024) and Addo and Auguste (2025) on the link between wealth, health, and life outcomes. Ashman and Neumuller (2020) show that when bequests are a luxury good, bequest motives greatly magnify the effect of racial income differences on median racial wealth gap.

[12] See Darity (1980), Bayer and Charles (2018), and Hurst, Rubinstein and Shimizu (2024) on the evolution of racial earnings differences. See also Kondo et al. (2024) on granular income and earnings distributions. Here, since we hew closer to the aggregate dynastic accounting approach in Derenoncourt et al. (2024), we do not include permanent income differences within or across groups.

gross return on household wealth $a > 0$ is $\left[(1+r) + \omega_{j,r} r \mathbb{1}_{a>\bar{a}_j}\right] a$. We also consider specifications with group-specific wealth taxes $\tau_{j,a}$, which imply group-specific interest rates $1+r_j = (1-\tau_{j,a})(1+r)$ for $a \leq \bar{a}_j$.

Downside Risk Wedge. Last but not least, we introduce downside risks to the asset. Standard models do not typically incorporate this downside risk channel or quantify its contributions to the dynamics of racial wealth disparities, especially at the left tail. In our setup, these downside risks take the form of wealth destruction shocks denoted by a binary random variable $d \in \{0, 1\}$. A group j household with assets $a > 0$ experiences a wealth destruction event $(d = 1)$ with a group-specific probability χ_j. When a wealth destruction event occurs $(d = 1)$, the household loses all its wealth a, operates for one period as a hand-to-mouth household, and starts the next period with a debt position $a' = \max\{-\kappa_j a, \underline{a}_j\}$. The $\max$ operator in the post-destruction debt formula guarantees the debt is not below the debt limit $\underline{a}_j$. Together, the parameters χ_j and κ_j govern the downside risks of the asset a, and κ_j amplifies the wealth-loss correlation.

It is important to note that "wealth destruction" or expropriation in the model should not be interpreted literally or in the same way across eras. In the model, it is simply a device to capture downside shocks to wealth. Another interpretation is an expenditure shock equal to $(a + \max\{\kappa_j a, -\underline{a}_j\})$ and occurring with probability χ_j. For example, Livshits, MacGee and Tertilt (2007), Chatterjee et al. (2007), and Braxton et al. (2024) rely on such shocks in the consumer debt literature. This interpretation may be more palatable in modern times, in contrast to the overt violence and injustice against Black lives and property under Jim Crow.[13]

2.2 Household Consumption-Savings Problem

We now formalize the recursive problem faced by households. Denote $s = (a, z, d) \in \mathcal{S}$, the state vector composed of the incoming wealth a, labor productivity draw z, a wealth destruction realization d of a household belong to group j. Given wages w and interest rate r, a j-household in state s solves the following problem:

[13] From a longer historical perspective, many events suggest that such destruction shock or wealth-loss correlation may have existed under Jim Crow for Black households in the U.S.–e.g., the Red Summer (see McWhirter, 2011), the racial massacre in Tulsa in 1921 (see Albright et al., 2021), and the case of lynchings against successful Black business owners (see Bair (2000) and Wells-Barnett (2002) on the case of Calvin McDowell, Thomas Moss, and Henry Stewart, who were lynched in Memphis, TN because of their successful grocery store).

$$V_j(a,z,d) = \max_{a' \in \mathcal{A}_j(s)} \Bigg\{ (1-d)\; u\Big(\overbrace{(1-\omega_{j,\ell})w\ell}^{y_j(s)} - a' + (1+r)a\,\mathbb{1}_{a<0} \\ + (1-\tau_{j,a})\Big[(1+r) + \omega_{j,r} r \mathbb{1}_{a>\bar{a}_j}\Big] a\,\mathbb{1}_{a>0}\Big) \\ + d\; u\Big((1-\omega_{j,\ell})w\ell\Big) \\ + \beta \mathbb{E}_{s'|s}\Big[V_j(a',z',d')|z\Big] \Bigg\}, \tag{2}$$

where $y(s) = (1-\omega_{j,\ell})\, wz\ell$ denotes labor earnings, z is a labor productivity shock following a Markov process with transition matrix $G(z',z)$, and $d \in \{0,1\}$ is a wealth destruction variable such that $\Pr[d=1|a] = \chi_j \mathbb{1}\{a>0\}$.

Asset Returns, Wealth Shocks, and Choice Sets. When no wealth destruction event occurs ($d=0$), the feasible set of savings a' spans the debt limit and the net worth:

$$\mathcal{A}_j(s) = \Big[\underline{a}_j, (1-\omega_{j,\ell})wz\ell + (1+r)a\,\mathbb{1}_{a<0} + (1-\tau_{j,a})\left(1+r+\omega_{j,r} r \mathbb{1}_{\{a>\bar{a}_j\}}\right) a\,\mathbb{1}_{a>0}\Big], \tag{3}$$

where $\underline{a}_j \equiv -\min_z (1-\omega_{j,\ell})wz\ell/r \leq 0$ is the natural debt limit, as in Aiyagari (1994).

However, when a wealth destruction even ($d=1$) occurs, the household consumes its earnings because of a temporary financial exclusion, loses all its wealth, and get an new debt position governed by the wealth-loss correlation parameter κ_j:

$$\mathcal{A}_j(s) = \Big\{ \max\{-\kappa_j a, \underline{a}_j\} \Big\} \qquad \text{when } d=1 \text{ and } a>0. \tag{4}$$

2.3 Partial Equilibrium Definition

Given wages w, an interest rate r, and group-specific frictions $\{\omega_{j,\ell}, \omega_{j,r}, \tau_{j,a}, \chi_j, \kappa_j\}$, a partial equilibrium is a collection of savings policy functions $g_{j,a}(\cdot)$ and value functions $V_j(\cdot)$ defined over the state space $\mathcal{S}$ such that $g_{j,a}$ and V_j jointly solve the household problem (2) for each group j.

These policy functions imply an equilibrium wealth distribution $\Gamma_j(\cdot)$ for the group j. The implied

beginning-of-period wealth distribution $\Gamma_j(\cdot)$ is defined over $\mathcal{S}$ and satisfies

$$\Gamma_j(a', z', d') = \iint_{a,z} \sum_d \mathbb{1}\Big\{g_{j,a}(a, z, d) = a'\Big\} \Pr[d'|a]\; G(z'|z)\, \mathrm{d}\Gamma_j(a, z, d)\,. \tag{5}$$

By using a partial equilibrium concept, we ignore the joint equilibrium determination of aggregate savings and interest rates. Since we are interested primarily in cross-group wealth differences, we think this is not a major drawback. The partial equilibrium approach also simplifies our computational strategy: we can treat each group as a separate island economy, without cross-group general equilibrium equations.[14]

2.4 Inferring Financial Frictions from the Data

Ideally, since the state in the model is $s = (a, z, d)$ for a j household, the model parameters–especially financial friction parameters–could be identified with household-level panel data on income, consumption, and wealth. One can only do so using a couple of datasets for recent years. However, we are interested in recovering *time-varying wedges* over a longer historical period. Since we lack such data going back in time, we use the cross-sectional wealth data assembled in Derenoncourt et al. (2024, 2023).

While the historical record does not give us wealth contingent on a state (s), the equilibrium distributions $\Gamma_j(a, z, d)$ can be aggregated into unconditional wealth distributions $\overline{\Gamma}_j(a)$ whose moments–e.g., the fraction of households with nonpositive wealth, the median wealth, or the 75th percentile of wealth–are shaped by the model parameters.

Our goal is to invert the model to match these observed wealth distribution moments and, thus, identify the financial friction parameters. But how do financial frictions shape wealth distributions?

First, one can see from the equilibrium wealth distribution definition (see equation 5) that the wealth destruction probability χ_j, through the term $\Pr(d|a)$, governs the left tail. However, the mechanics of the model are more intertwined. In particular, when $d = 1$, the wealth-loss correlation coefficient κ_j, through the policy function $g_{j,a}$, also shapes the left tail. Moreover, all financial frictions interact to shape the policy function for savings. In fact, from equations 2 and 3, one can see that the expected return on

[14] In Boerma and Karabarbounis (2023), the response of the interest rate is a key determinant of the effects of a one-time wealth transfer on long-run wealth convergence or divergence.

holding asset $a \in (0, \min\left\{-\frac{a_j}{\kappa_j}, \overline{a}_j\right\}]$ is

$$(1-\tilde{\chi}_j)(1+r) \text{ such that } \tilde{\chi}_j = \chi_j\left(1+\frac{\kappa_j}{1+r}\right). \tag{6}$$

This expected return term shows that the equilibrium cross-sectional wealth distribution in the model arises partly from the interplay of all the parameters operating as a wealth tax $\tilde{\chi}_j$. However, since the asset is risky and markets are incomplete, the expected return term does not summarize all the effects of the financial frictions. The downside risk channel creates the working of two opposite forces across the entire wealth distribution. On the one hand, the destruction must be small to allow significant accumulation of wealth relative to income, in order to match the intensive margin at the median and top quartile. On the other hand, the downside risk should be sizable enough to generate enough hand-to-mouth households, as observed in the data.[15]

3 Using the Model to Construct a Path of Wedges

3.1 Baseline Calibration Strategy

We now use the model to estimate a path of frictions $\left\{\omega^t_{j,\ell}, \chi^t_j, \kappa^t_j, \omega^t_{j,r}\right\}$, where t denotes time, that account for the evolution of income and wealth dynamics by race since 1860.[16]

Our accounting exercise is deliberately parsimonious, as we aim to highlight how these simple, historically plausible channels of racial exclusion and wealth downside risks can account for the observed evolution of racial wealth inequality from 1860 to 2020. We rely on standard preference parameters from the literature, and calibrate labor and capital market frictions to match key moments of consistently available data series.

We follow a bi-decadal calibration strategy: changes in frictions occur every 20 years and are "MIT" shocks; that is, agents in the model do not expect prevailing conditions to change. To be precise, for each bi-decadal window $v_T = \left\{T-20, \ldots, T\right\}$ — with end years $T = 1880, 1900, 1920, 1940, 1960, 1980,$

[15] We conduct alternative calibration exercises in Section 4, using a wealth-tax-only model, and we show that incorporating extensive margin dynamics is key for identifying downside financial risk frictions.

[16] We do not estimate wealth taxes $\tau^t_{j,a}$ in our baseline estimation, since the group-specific excess return premium $\omega^t_{j,r}$ already operates as a safe return wedge. Still, for the baseline calibration, we report the wealth tax interpretation $(\tilde{\chi}_j)$ of the expected return implied by the frictions χ_j and κ_j. We estimate wealth taxes $\tau^t_{j,a}$ in alternative calibrations in Section 4.

2000, 2020 — we take as given the bi-decade's initial wealth distribution $\overline{\Gamma}_{j,T-20}$ from the data. The model is calibrated *for each window* and *for each group* to match selected income and wealth dynamics, and yields a path of time-varying group-specific wedges $\left\{\omega_{j,\ell}^{v_T}, \chi_j^{v_T}, \kappa_j^{v_T}, \tau_{j,a}^{v_T}, \omega_{j,r}^{v_T}\right\}_T$.

We take mean income dynamics from the data to calibrate the path of earnings wedges $\left\{\omega_{j,\ell}^{v_T}\right\}$. We estimate the remaining set of financial friction dynamics $\left\{\chi_j^{v_T}, \kappa_j^{v_T}, \tau_{j,a}^{v_T}, \omega_{j,r}^{v_T}\right\}$ by matching observed wealth distribution dynamics. We simulate the model for each bi-decade period, starting with the initial wealth distributions observed in the data. We target wealth distribution outcomes after 20 years, as opposed to long-run distributions. Thus, initial conditions also matter.

3.2 Functional Forms and Baseline Parameters

A period in the model is a year. All households in the economy have a common discount factor β and common preferences over consumption, which are defined by a CRRA period utility function u: $u(c) = \frac{1}{1-\sigma}c^{1-\sigma}$. We assume that the idiosyncratic income shock process z is also common across groups and follows an auto-regressive process with persistence ρ_z and innovation volatility σ_z; that is, $z' = \rho_z z + \varepsilon_z$, where $\varepsilon_z \sim \mathcal{N}(0, \sigma_z^2)$.[17]

Table 1: Externally Set Parameters

	Parameter	Value	Note
Risk aversion	σ	2	Standard – Aiyagari (1994)
Discount factor	β	0.99	–
Interest rate	r	0.04	–
Income – persistence	ρ_z	0.96	Storesletten, Telmer and Yaron (2004)
Income shocks – std. dev.	σ_z	0.02	Storesletten, Telmer and Yaron (2004)
Earnings	$w\ell$	1	in units of mean W annual earnings

Table 1 summarizes the set of parameters that we externally calibrate, using standard values from canonical models in the literature. Following Aiyagari (1994), we set $\beta = 0.99$ given our annual model, and choose a standard risk aversion value of $\sigma = 2$. We follow the results of the estimation

[17] We can certainly incorporate richer labor income processes over time and across groups. However, it is not easy to find consistent historical income data to estimate richer time-varying income processes.

in Storesletten, Telmer and Yaron (2004) and set the persistence of the idiosyncratic income risk to $\rho_z = 0.96$ and its conditional variance to $\sigma_z^2 = 0.02$. Finally, the interest rate is set to $r = 4\%$ as we adopt a partial equilibrium approach. We do not let these externally calibrated parameters vary over time, in order to have a simpler interpretation of the time-varying group-specific wedges we estimate.

3.3 Data Moments and Simulation Targets

Our primary data sources are the Survey of Consumer Finances–specifically, the harmonized "SCF+" version, constructed by Kuhn, Schularick and Steins (2020)–along with the wealth series assembled by Derenoncourt et al. (2024, 2023), which goes back to 1860. We use these sources for consistency and coverage. The wealth and income data series we use are all inflation adjusted to 2019 dollars.[18]

Labor Earnings Wedges. For each bi-decadal window $v_T = \Big\{T - 20, \ldots, T\Big\}$, with end years $T = 1880, 1900, 1920, 1940, 1960, 1980, 2000, 2020$, we normalize earnings by setting $w\ell$ to 1 and $1 - \omega_{W,\ell}^{v_T} = 1$, effectively measuring all incomes and wealth in the model in units of average White household earnings during the analysis window. With this normalization, we scale income and wealth measures by dividing them by the (end of) bi-decade mean White household earnings. We then set $\omega_{B,\ell}^{v_T}$ to match the end-of-bi-decade ratio of average Black-White household earnings.[19] That is,

$$1 - \omega_{B,\ell}^{v_T} = \frac{\text{mean Black household earnings}_T}{\text{mean White household earnings}_T}.$$

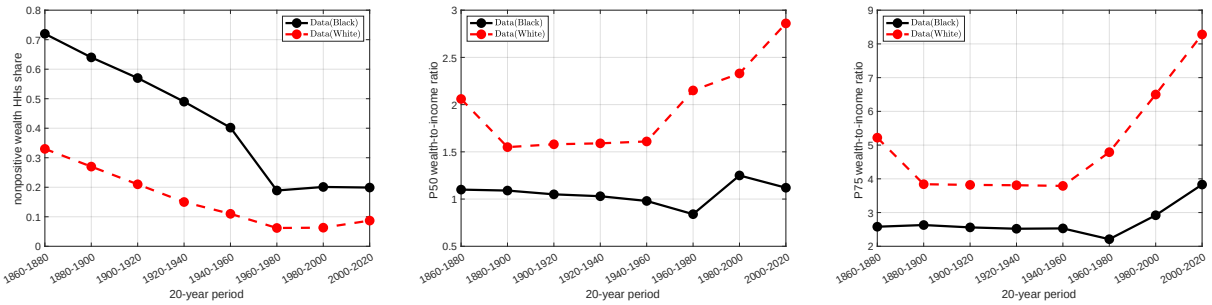
Target Wealth Distribution Moments and Dynamics. Figure 2 summarizes the group-specific bi-decadal wealth moments (rescaled into wealth-to-income ratios) that we target. Figure 2 shows dramatic racial gaps in the share of households without positive wealth (panel a), the wealth-to-income ratios at the median (panel b), and at the top quartile (panel c). These group-level terms mirror the extensive and

[18] In the SCF+, we define White households as those where the head of the household identified as White and non-Hispanic, while Black households are defined as those where the head of the household identified as Black. Our measure of household wealth in the SCF+ is based on the household net worth variable (*ffanw*). Our measure of total household (noncapital) income in the data includes household income from wages, salaries, and self-employment. This income measure therefore captures differences between Black and White households in employment rates, wage rates, hours, returns to occupation, industry, education, or tenure, and also differences in self-employment income in the postwar era covered by the SCF+. We exclude all observations with negative income.

[19] When we have richer SCF+ data in the latter part of the sample, we use the broader concept of non-capital income, since our main goal with earnings is not to include capital income. See Darity (1980) for a cautionary account of the risk of inferring too much progress when one does not take into account non-wage earners. Our estimation results are broadly robust to alternative labor income wedge paths with less convergence during the Civil Rights era.

intensive margins of the decomposition in the introduction (see equation 1 and Figure 1).

Figure 2: Zero Wealth Shares and Wealth Dynamics by Group



(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

Note: We compute the wealth percentiles among group $j = B, W$ households with positive wealth. We divide the wealth percentiles by average household earnings in the group, using end of window values. Source: Authors' calculations using Derenoncourt et al. (2023, 2024) and Kuhn, Schularick and Steins (2020) replication datasets.

The fraction of Black households without positive wealth fell from almost three-fourths in 1880 to one-fifth in 2020, with a historic decline during the Civil Rights era. For White households, the fraction of nonpositive wealth households also fell, from one-third in 1880 to one-tenth by 2020. Wealth-to-income ratios too are consistently higher for White households, compared with those for Black households. The ratios for the two groups significantly diverged after the Civil Rights era. For example, from 1960 to 2020, the median wealth-to-income ratio increased from one and a half to three for White households, while it fluctuated around one for Black households. At the top quartile too, the ratio doubled from four to eight for White households, but grew from only two and a half to four for Black households.

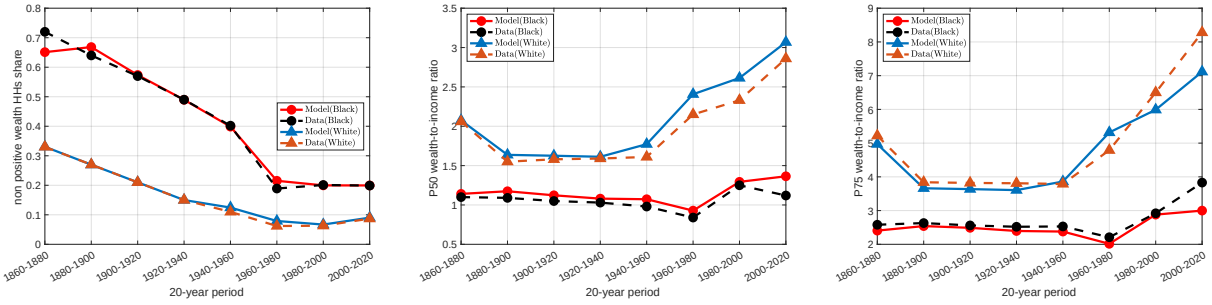
Initial Wealth Distributions. Initial conditions matter in our calibration, since we target wealth distributions after 20 years as opposed to the long run. We choose parameters of a mixture distribution to match moments of the initial wealth distribution $\overline{\Gamma}_{j,T-20}$. The parameters of the group j mixture at the beginning of the bi-decade $v_T = \{T-20, \ldots, T\}$ are calibrated to match, at $T-20$: the share of households without positive wealth, the median value of positive wealth (scaled by mean White household earnings at T), and two positive wealth percentile ratios (P50-over-P25, and P90-over-P75).[20]

Simulated Wealth Moments. We internally calibrate each group j's economy for each 20-year window $v_T = \{T-20, \ldots, T\}$ by setting prevailing financial frictions $\{\chi_j^{v_T}, \kappa_j^{v_T}, \omega_{j,r}^{v_T}\}$ through model simulations

[20] In Appendix F.2, we define the mixture of uniform, lognormal, and Pareto distributions that we construct to capture the moments characterizing the initial wealth distributions.

to match selected moments of the wealth distribution $\overline{\Gamma}_{j,T}$ (scaled by mean White household earnings at T) at the end of the bi-decade. Specifically, given the initial wealth distributions at the beginning of the bi-decade, and the earnings wedge $\omega_{j,\ell}^{v_T}$, we choose the financial frictions tuple for group j that minimizes deviations from the wealth distribution moments we target at the end of the bi-decade (see Figure 2): the share of households with nonpositive wealth, the positive median wealth-to-income ratio, and the positive 75^{th} percentile wealth-to-income ratio.

Figure 3: Wealth Distributions: Fit by Group

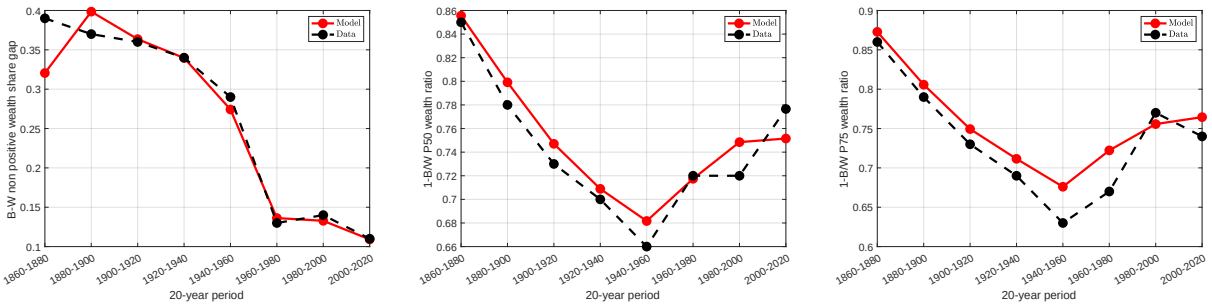


(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

3.4 Model Fit Within and Across Groups

Intragroup Wealth Distributions Dynamics. Panel (a) of Figure 3 shows that the model almost perfectly captures the extensive margin in the data–namely, the share of households with nonpositive wealth in both groups. In panels (b) and (c), the model does a very good job of replicating the intensive margin at the median and the top quartile of the wealth distribution, measured by the wealth-to-income ratio. The model slightly underestimates the recent rise in top wealth inequality among White households.

Figure 4: Wealth Distributions: Fit – Gaps Across Groups



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Wealth Distribution Differences Across Groups. Figure 4 shows that the model does a good job of capturing the Black-White wealth gaps, inheriting the good fit of intragroup wealth distributions in Figure 3. Panel (a) reflects this good fit for the extensive margin Black-White gap. Similarly, one would mechanically expect a good fit for the intensive margin moments: panels (b) and (c) of Figure 4 show the relative Black-White wealth ratio at the median and at the top quartile of the positive wealth distribution. Overall, the model delivers the relative wealth dynamics observed since 1860, even though it slightly underestimates the racial wealth gap.[21]

3.5 Calibrated Financial and Labor Wedges: 1860 – 2020

Table 2 and Figure 5 show the Black-White differences in the calibrated wedges. The values are reported in percentage points, and the $\Delta_{\text{B-W}}$ operator denotes the Black-White difference in the given bi-decade; that is, $\Delta_{\text{B-W}}\, \omega_\ell^{v_T} \equiv \omega_{B,\ell}^{v_T} - \omega_{W,\ell}^{v_T}$. The underlying group-specific values of the calibrated wedges are reported in Appendix B.

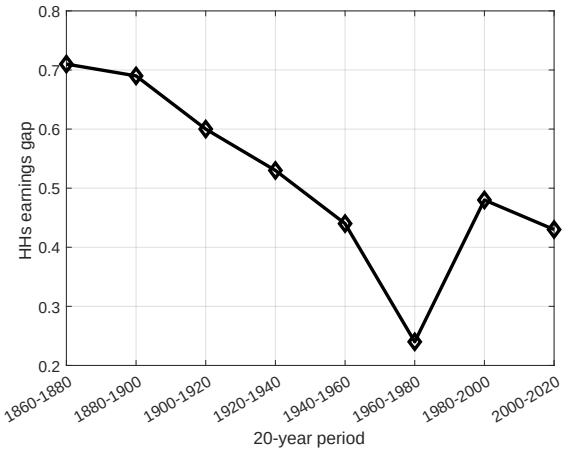
Racial Earnings Gaps. Racial earnings gaps are reported in the top panel of Table 2 and in panel (a) of Figure 5. Note that the earnings wedges are taken directly from the data. As is consistent with the literature, the relative Black-White earnings gap significantly fell, from 70% post-Emancipation to 20% at the end of the Civil Rights movement. The post-Civil Rights era experienced a significant rollback in income convergence.[22]

Racial Gaps in Financial Downside Risks. The frictions in the financial markets are captured by the downside risk parameters and the excess return wedges. We report racial gaps in these wedges in the second panel from the top in Table 2. The Black-White gap in wealth destruction probabilities (see panel (b) of Figure 5) is large and stable over time, though there is notable spike in 1960–1980 around the Civil Rights era. The second layer of downside risk is the wealth-loss correlation. The Black-White gap in wealth-loss correlation (see panel (c) of Figure 5) subsides after 1960, after a century of a

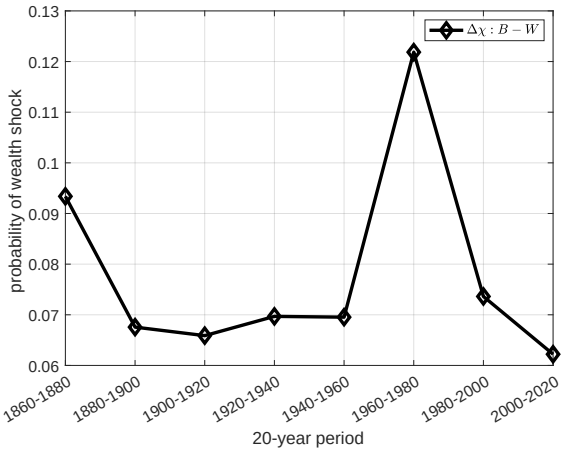
[21] Since we take income dynamics $(\overline{y}_B/\overline{y}_W)$ from the data and calibrate the model to match wealth-to-income ratios $(\overline{a}_{j|a>0}/\overline{y}_B)$, we mechanically match for the Black-White wealth ratios $\overline{a}_{B|a>0}/\overline{a}_{W|a>0}$.

[22] The racial earnings convergence varies somewhat across sources. See Darity (1980), Bayer and Charles (2018), and Kondo et al. (2024). Derenoncourt and Montialoux (2020) document significant racial earnings convergence from the 1966 Fair Labor Standards Act extension of federal minimum wage coverage. Our results are robust to more modest earnings convergence around the Civil Rights era.

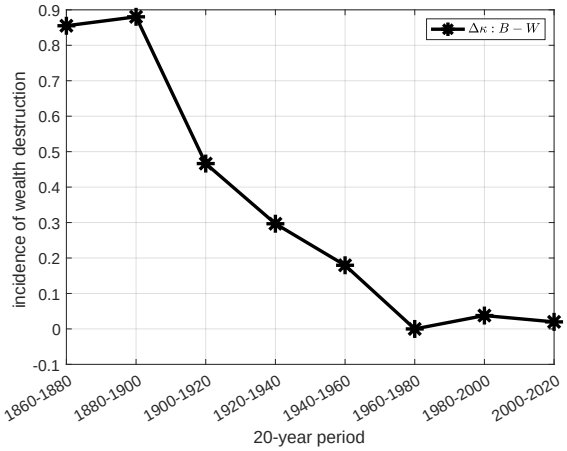
Figure 5: Calibrated Wedges – Gaps Across Groups



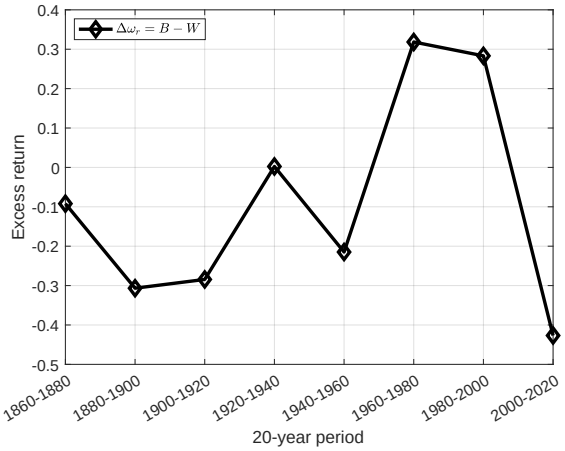
(a) Earnings B-W relative gap



(b) Wealth destruction probability B-W gap



(c) Wealth-loss correlation B-W gap



(d) Top wealth excess return B-W gap

Table 2: Calibrated Wedges – Gap Across Groups

Wedge gaps (B – W, in %)	1860 to 1880	1880 to 1900	1900 to 1920	1920 to 1940	1940 to 1960	1960 to 1980	1980 to 2000	2000 to 2020
				Earnings wedge				
$\Delta_{\text{B-W}}\,\omega_\ell$	71.0	69.0	60.0	53.0	44.0	24.0	48.0	43.0
				Downside risk wedge				
$\Delta_{\text{B-W}}\,\chi$	9.3	6.8	6.6	7.0	6.9	12.2	7.3	6.2
$\Delta_{\text{B-W}}\,\kappa$	85.5	88.0	46.6	29.2	17.9	0.0	3.8	1.9
				Excess return wedge				
$\Delta_{\text{B-W}}\,\omega_r$	-9.2	-30.6	-28.5	0.2	-21.5	31.9	28.3	-42.7
				Expected wealth tax				
$\Delta_{\text{B-W}}\,\tilde{\chi}$	26.1	23.5	15.5	12.5	10.2	12.2	7.9	6.6

Note: We report the racial gap in the calibrated wedges as their Black-White difference. For group-specific values for each wedge parameter, please refer to Table B1 in Appendix B. All gaps reported in the table are in percentage points.

significantly large, but declining, gap which hurt Black wealth accumulation.

In contrast to shrinking racial earnings gaps and vanishing wealth-loss correlation gaps, the Black-White wealth destruction gap spiked in 1960–1980 because of two offsetting diverging forces. First, among Black households, a high wealth destruction probability is still estimated in order to rationalize lower-but-still-elevated shares of zero wealth Black households. Second, among White households, financial frictions are calibrated to have significantly eased around that time, owing to higher wealth-to-income ratios.[23]

To summarize these different dimensions of financial frictions, we compute an implied expected return gap $(\Delta_{\text{B-W}}\tilde{\chi})$ in the bottom row of Table 2. Overall, this synthetic downside risk gap falls steadily because declining racial wealth-loss correlation gaps since 1860, and a fall in the racial wealth destruction gap following its spike in 1960–1980. By 2020, wealth-loss correlations have converged, and the racial wealth destruction probability gap falls to approximately 6 percentage points. Yet, the Black wealth

[23] Other important societal changes were occurring during the 1960–1980 window. Examples include the Vietnam War, rising inflation, and massive and widening polarization. Also, "from 1960 to 1970, 2.1 million white people left American cities for the suburbs while 2.6 million African Americans moved into the nation's cities" (Taylor, 2019, pg. 106). Jobs and businesses too moved to the suburbs (Miller, 2023).

destruction probability remains twice ($\frac{\chi_B}{\chi_W} = \frac{12.7}{6.5} \approx 2$) as large as White households' estimates.

Racial Excess Return Gaps. Finally, we report the model-implied dynamics for the excess return gap ($\Delta_{\text{B-W}}\omega_r$) in the third panel from the top of Table 2 and in panel (d) of Figure 5. The excess return is typically higher for top wealth quartile White households than top quartile Black households, except in 1960–1980 and 1980–2000. The Black-White racial gap in excess return is also more volatile after 1960: it turns positive in 1960–1980, precisely when the wealth destruction gap spikes, but becomes negative again in 2000–2020. By 2020, the calibrated Black-White excess return gap fell to -1.7%: the top excess wealth return for White households is more than twice the excess return for Black households, the largest gap across periods.[24]

Temporally Correlated Wedges. The time series of the individual wedges estimated suggest that their temporal correlation is important to understand the dynamics of racial wealth inequality. We measure the pairwise correlations within and across groups of the calibrated wedges in Table 3, where the Δ_t operator denotes the bi-decadal change, that is, $\Delta_t \omega_{B,\ell}^{v_T} \equiv \omega_{B,\ell}^{v_T} - \omega_{B,\ell}^{v_T-20}$. The calibrated model not only rejects that only one wedge is active at a time but also confirms that some wedges co-move systematically within or across groups over time.

In particular, we note a large negative correlation between changes in $\omega_{B,\ell}^{v_T}$ and changes in $\chi_B^{v_T}$: $\text{corr}(\Delta_t \omega_{B,\ell}, \Delta_t \chi_B) = -.89$. In other words, improvements in the Black-White earnings gap are correlated with a worsening of estimated wealth destruction risk for Black households. Since we have estimated only seven bi-decadal changes, these correlations should be taken with a grain of salt, however. This is also an important caveat since we noted that the Civil Rights era dynamics are large and potentially driving the magnitude and sign of the correlations we estimate.

3.6 Potential Interpretations and Historical Lens on the Wedges

Across episodes, identifiable historical factors exist that bolster the finding that wealth loss risk is higher for Black Americans than for White Americans. It is important to discuss the historical plausibility of

[24] Given the model formulation, we compute the gap as $\Delta_{\text{B-W}}\omega_r \times r = (.28 - .71) \times 4\% \approx -1.7\%$. It is important to note that our calibration choices perhaps make the excess return $\omega_{j,r}$ less comparable across groups than the other frictions. Instead of a common cutoff across groups, we set group-specific cutoffs for the excess return in order to better identify *within-group* wealth inequality.

Table 3: Pairwise Correlations in Black and White Wedge Dynamics

	$\Delta_t\omega^B_{\ell,t}$	$\Delta_t\omega^B_{r,t}$	$\Delta_t\chi^B_t$	$\Delta_t\kappa^B_t$	$\Delta_t\omega^W_{r,t}$	$\Delta_t\chi^W_t$	$\Delta_t\kappa^W_t$
$\Delta_t\omega^B_{\ell,t}$	1	-0.26 (0.57)	-0.89 (0.00)	-0.54 (0.21)	-0.31 (0.50)	-0.39 (0.38)	-0.19 (0.69)
$\Delta_t\omega^B_{r,t}$		1	0.65 (0.84)	-0.14 (0.77)	0.70 (0.08)	0.90 (0.00)	-0.60 (0.16)
$\Delta_t\chi^B_t$			1	0.32 (0.23)	0.57 (0.90)	0.66 (0.96)	-0.08 (0.35)
$\Delta_t\kappa^B_t$				1	0.32 (0.48)	0.20 (0.66)	0.61 (0.15)
$\Delta_t\omega^W_{r,t}$					1	0.84 (0.02)	0.12 (0.80)
$\Delta_t\chi^W_t$						1	-0.34 (0.45)
$\Delta_t\kappa^W_t$							1

Note: Each cell of the table represents a pairwise correlation within or across groups of the calibrated wedges in Table 3, where the Δ_t operator denotes the bi-decadal change; i.e., $\Delta_t\omega^{v_T}_{B,\ell} \equiv \omega^{v_T+20}_{B,\ell} - \omega^{v_T}_{B,\ell}$. We report the $p-$values in parentheses.

the estimated frictions and revisit their alternative interpretations, since we view the model primarily as an accounting device to help inform future work on the dynamics of racial wealth differences.[25]

Risky Black Wealth Under Jim Crow. One salient feature of estimated wedges is the significant and large wealth-loss correlation for Black households before 1960. Focusing on the Jim Crow era, Albright et al. (2021) study the persistent effects of the Tulsa Massacre, which occurred in 1921, on Black homeownership and livelihood. They find large and persistent declines in homeownership and white-collar jobs not only among Black residents of Tulsa, but also among Black Americans in cities that received newspaper coverage of the Tulsa Massacre. Pointing more directly to the larger wealth-loss correlation we document for Black households in this era, Albright et al. (2021) also show that Black Tulsans selectively migrated out of Tulsa: Black households that owned a home or that had a white-collar jobholder were more likely to out migrate following the Tulsa Massacre.[26]

[25] In the tradition of Chari, Kehoe and McGrattan (2007), the frictions we estimated do not have an absolute meaning, only a clear mechanical function in the context of the model. Chari, Kehoe and McGrattan (2007) illustrate how wedges can also be used to map outcomes across models. Similarly, we argue our results points to the *class* of channels or models that may deliver observed racial wealth dynamics, especially at the left tail. For example, Tan and Zeida (2024) find that, relative to White-owned startups, Black-owned startups face persistently lower consumer demand, along with lower initial credit supply.

[26] In 1892, anti-Black violence also caused the out-migration of hundreds of Black residents from the Curve neighborhood in Memphis. Many businesses and households were raided in the neighborhood, following an original raid on the People's Grocery store. Thomas Moss, a postman and co-owner of the People's Grocery, "pleaded with his abductors to spare his life on behalf of his wife and children, including his young daughter Maurine and the unborn baby his wife was carrying. His

The sizable Black wealth-loss correlation risk during the Jim Crow era may also reflect the experience of successful Black individuals who faced expropriation risk. Cook (2014) shows that the lynching of Black people, and other types of anti-Black violence, halted patenting by Black inventors in the Jim Crow era. Kahrl (2024) provides excellent historical evidence on tax assessments that deliberately trapped Black homeowners in vicious debt cycles or caused property loss–in some cases, for entire Black towns.

The model estimates show that while the wealth-loss correlation is virtually zero in the postwar era, the wealth destruction risk gap spiked in 1960 – 1980. Despite significant progress from the Civil Rights movement, the 1960s also ushered a new era of reversals punctuated by racial uprisings and riots. According to Collins and Margo (2007), "the course of racial politics in the United States changed abruptly between the passage of the Civil Rights Act of 1964 and the Fair Housing Act of 1968." Using city-level data on more than 700 civil disturbances between 1964 and 1971, they find that Black-owned property values fell more between 1960 and 1980 in areas that faced more severe disturbances. This uptick is in line with the spike in racial wealth destruction gap we estimate. Taylor (2019) too views this era as the rise of *predatory financial inclusion*: no longer explicitly excluded by race, but financially segregated based on spatial and socio-economic correlates of race.

The New Jim Crow: An Incarceration Channel? While the decline in racial labor market convergence after 1980 has been studied in the literature (see, for example, Bayer and Charles, 2018), downside risks may function less directly than they did under Jim Crow laws. One potential channel for downside risk differences between Black and White households after 1980 might be the "new" Jim Crow: the mass incarceration of Black Americans (see Alexander, 2020).[27]

Finlay, Mueller-Smith and Street (2023), using a novel administrative dataset, document a significantly larger exposure of Black youth to the criminal justice system and find that increased exposure is associated with lower or more fragile well-being outcomes.[28] Chiteji (2021) also finds that formerly incarcerated Black and Latino men exhibit scarring labor market effects from incarceration and hold significantly

plea was ignored, and when asked for a final statement before he was shot to death, he said: 'Tell my people to go West – there is no justice for them here."' Ida B. Wells who was Maurine's godmother also left Memphis after her newspaper office, *Memphis Free Speech*, was ransacked for her anti-lynching editorials. (Bair, 2000)

[27] Muller (2021) traces the historic and significant rise from the late 1970s to the early 1980s in the incarceration rates for Black Americans compared to White Americans.

[28] Deshpande and Mueller-Smith (2022) also show that loss of welfare benefits is associated with greater incarceration risk, primarily among Black youth.

less wealth in their "golden years."[29]

More directly, Maroto and Sykes (2020) document, using longitudinal survey data, that incarceration lowers not only income but also wealth accumulation and marriage opportunities. Humphries et al. (2025) leverage novel administrative data linkages and find that incarceration persistently lowers home-ownership and college enrollment. Thus, higher rates of incarceration act systemically as greater wealth downside risks too.[30]

Assessing Contemporary Racial Gaps in Financial Wedges. How do these financial wedge gaps compare in magnitude with recent findings in the literature? For comparison, Kermani and Wong (2024) show, using transaction-level data from 1990 to 2020, that Black homeowners experience distress sales at twice the rate of White homeowners. All told, Kermani and Wong (2024) find that Black homeowners have unlevered and levered returns that are respectively about 1.3 and 2.5 percentage points lower per year than White homeowners; this difference is driven mainly by the incidence and intensity of distressed sales.[31] Argyle et al. (2025) also find significant contemporary racial disparities in access to debt relief: across Chapter 13 consumer bankruptcy filers since 2008, Black filers are 5.6 percentage points more likely to have their cases dismissed without debt relief (compared with White filers).[32] Avenancio-León and Howard (2022), using property-level data from 2003 to 2013, show that Black and Hispanic residents face property tax assessments that are 10 percentage points higher than those of White residents.

These contemporary estimates broadly suggest, like our calibrated racial gaps in financial wedges after 1960, that downside wealth risks are still materially larger for Black households. We present additional evidence on downside risks faced by Black homeowners in Section 6.

[29] Gordon et al. (2023) also find that incarceration begets large labor market scarring effects. Imrohoroglu, Kumru and Lian (2025) study racial wealth disparities arising from Black-White differences in income-generating property crime activity and the incidence of incarceration risk.

[30] Chiteji and Hamilton (2002), Heflin and Pattillo (2002) and Heflin and Chiteji (2014) show that perceived obligations to kin in need or in poor health are also an important determinant of wealth. The role of financial ties and extended kinship networks is not explicitly modeled in our setup. The wealth destruction shock can certainly be interpreted as a kinship network expenditure shock.

[31] See "LTV" specifications in Table 1 of the online appendix in Kermani and Wong (2024).

[32] Argyle et al. (2025) show that "Black filers facing White trustees face payments plans requiring an additional $2,000 over five years," which lead to missed payments and dismissal.

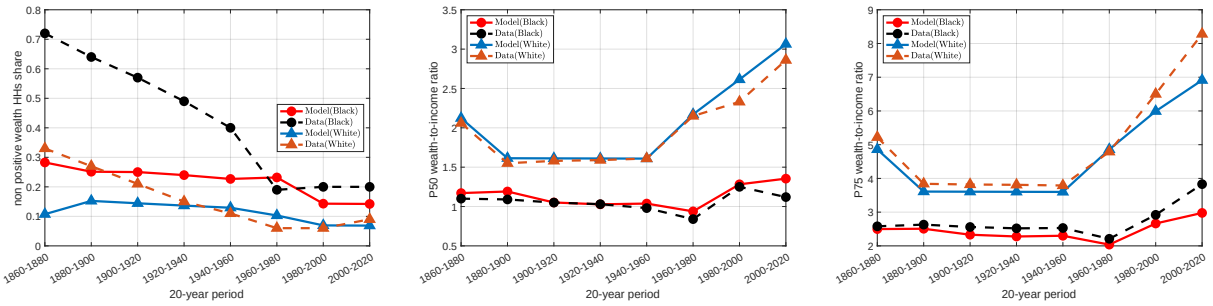
4 Unpacking the Mechanism and Calibrated Wedges

Our baseline model introduces capital market frictions through the channel of a group-based downside risk wedge. In this section, we explore the robustness of this mechanism in rationalizing the racial wealth gap in the data. To this end, we consider an alternative version of the model, where the presence of the downside risk wedge is contrasted with a wealth tax. We then discuss the contributions of these wedges to different dimensions of racial wealth disparities over time in the following section.

4.1 Does the Wealth-Loss Correlation Matter?

In our exposition of the model in Section 2, we assume that the household loses all its wealth a when the wealth destruction event occurs, and that it starts the next period with a debt position $a' = \max\{-\kappa_j, \underline{a}_j\}$. Therefore, it is worth investigating the importance of this channel. We re-calibrate the model with group-specific destruction (χ_j) and excess return $(\omega_{r,j})$, but no wealth-loss correlation when wealth destruction occurs $(\kappa_j \equiv 0)$.

Figure 6: Extensive and Intensive Margins Without Wealth-Loss Correlation



(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

We target group-specific wealth-to-income ratios (intensive margin), and the results are shown in Figure 6. In panels (b) and (c), the model matches the data well along the intensive margin at the median and the 75^{th} percentile of the positive wealth distribution. However, panel (a) shows the share of households with nonpositive wealth predicted by the model without wealth-loss correlation is too low, especially in the decades between Emancipation and the Civil Rights era.[33]

[33] It may seem trivial to have a good fit along the intensive margin, as we target the median and the 75^{th} percentile of the positive wealth distribution. However, when we target both the extensive margin and the 75^{th} positive wealth percentile, the model fails to match the 75^{th} positive wealth percentile for the Black group. See the additional results in Figure B2 in Appendix B.

This suggests that the wealth destruction probability, on its own, is not enough to jointly deliver the large left tail observed in the early decades for Black households and their relative wealth when holding positive wealth. In fact, the wealth destruction probability (χ_j) regulates flows *into* the left tail, but it is too blunt for governing left tail outflows. An increase in the wealth destruction probability (χ_j) shifts the positive wealth distribution to the left, increasing the share of households with nonpositive wealth. However, a high wealth destruction probability also lowers expected returns and thereby reduces wealth holdings. One can think of the wealth-loss correlation κ as a device that regulates flows of both *out of* and *into* positive wealth. In fact, with a higher wealth-loss correlation (κ_j), the exit rate from the nonpositive wealth region falls, which means a lower probability of destruction is needed to match the data without compromising the intensive margin.[34]

4.2 Isn't a Wealth Tax Without Downside Risk Su cient?

Do we really need a downside risk wedge in the first place? Given the historical unequal tax assessments experienced by Black homeowners relative to their white counterparts (Avenancio-León and Howard, 2022; Kahrl, 2024), it is intuitive to suggest that a model with a wealth tax could help rationalize the empirical racial wealth gap. This view is consistent with the notion of risk-adjusted wealth tax, $\tilde{\chi}$ introduced in Equation 6 of Section 2.4. We implement this idea by recalibrating the model with group-specific wealth taxes ($\tau_{j,a}$) and excess returns ($\omega_{r,j}$), but without downside risk wedges ($\chi_j \equiv 0, \kappa_j \equiv 0$). As in the previous exercise, we target group-specific wealth-to-income ratios.[35]

The racial differences in calibrated wealth taxes are summarized in the first row of Table 4 and shown in Figure 7. In the second row of Table 4, we also report the racial differences in the risk-adjusted wealth tax rates derived from the baseline model.

Black households face wealth tax rates that are on average 3.5 percentage points higher than their white counterparts. However, wealth taxes and composite risk-adjusted taxes differ significantly. First, the racial differences in risk-adjusted wealth taxes are consistently higher than the calibrated wealth

[34] This interpretation also suggests that we could have operationalized the wealth-loss correlation using κ as the probability of staying financially excluded from holding positive wealth, following the default risk literature. We think this alternative modeling is promising, especially if one wants to explicitly model assets and debt. We leave this exploration for future work. The current formulation more closely follows the workhorse Aiyagari (1994) model.

[35] Boerma and Karabarbounis (2023) and Imrohoroglu, Kumru and Lian (2025) rely instead on non-homothetic Stone-Geary preferences to rationalize the left tail of wealth. Puig (2024) uses a model with group-specific conspicuous consumption motives to deliver lower savings for Black households, compared with White households' savings.

Table 4: Calibrated Wealth Taxes – Gaps Across Groups

Wedge gaps (B – W, in %)	1860 to 1880	1880 to 1900	1900 to 1920	1920 to 1940	1940 to 1960	1960 to 1980	1980 to 2000	2000 to 2020
$\Delta\tau_a$	4.9	3.5	3.3	3.1	1.7	3.1	3.1	4.6
$\Delta\tilde{\chi}$	26.1	23.5	15.5	12.2	10.2	12.2	7.9	6.7

Note: We report the racial gap of all wedges as the difference between Black and White households. Risk-adjusted wealth taxes are derived using Equation 6 in Section 2.4. For the sake of exposition, we do not report the other calibrated wedges in this table. The group-specific levels are reported in Appendix B. All parameters are in percentage points.

Figure 7: Wealth Tax and Risk-Adjusted Wealth Tax – Gaps Across Groups

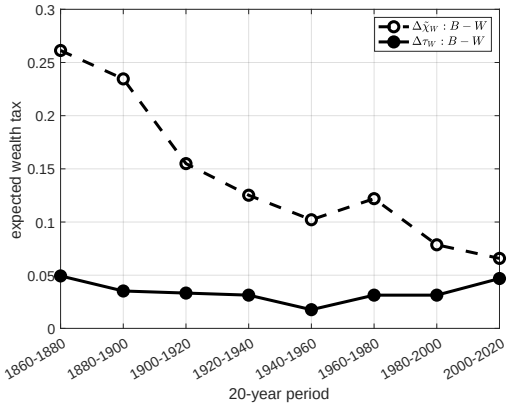
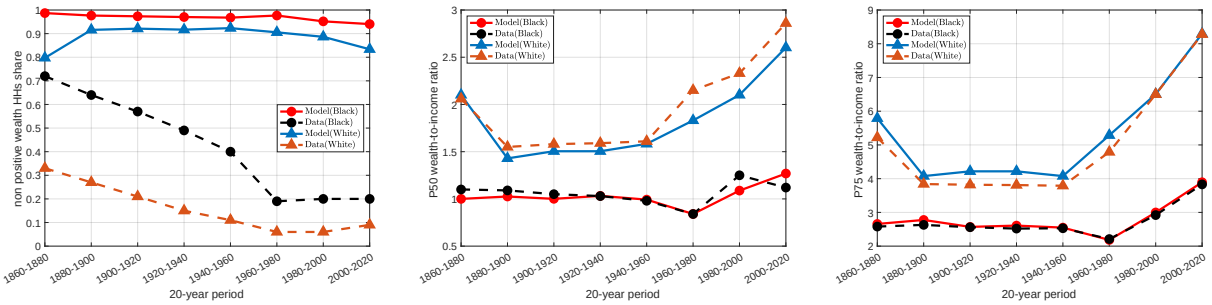


Figure 8: Extensive and Intensive Margins with Wealth Tax



(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

taxes over time, even in recent decades, when the wealth-loss correlation gaps are almost zero. Risk-adjusted wealth tax gaps are 1.5 to 6 times wealth tax gaps: the amplification stems from the baseline model requiring both higher destruction probability and wealth-loss correlation to match the initially high shares of hand-to-mouth households. Second, risk-adjusted tax differences display a decreasing pattern over time and closer to wealth tax gaps in recent decades.

However, the wealth-tax-only model is noticeably different from the baseline model, even in recent decades. Figure 8 illustrates the fit of the wealth tax model calibration. The model replicates the dynamics of the intensive margin (wealth-to-income ratios) at the median and top quartile over time (panels b and c). However, if we look at the share of households with nonpositive wealth shown in panel (a), we see that the wealth tax model fails drastically. The wealth-tax-only model fails to account for the empirical extensive margin, as the shares of households with nonpositive wealth are far off for both groups.[36] To understand the issue, it is important to note that the wealth-tax-only model reduces to a standard partial equilibrium Aiyagari (1994) economy with very high taxes, which makes savings significantly low only for a selected few high-income households.

5 Contributions of Wedges to the Racial Wealth Gaps

Equipped with a model calibrated to match key dimensions of wealth inequality, we now examine the contribution of each wedge to racial wealth gaps along the wealth distribution, both at the extensive and the intensive margin. Naturally, there are several ways to implement this type of decomposition. We focus on two main approaches.

In the first approach, we keep only one wedge active and re-simulate each bi-decade, with *changes* for all other frictions set to zero. Note that in this scenario, we reset the initial wealth distribution every two decades to capture the underlying changes that occurred in the preceding bi-decade, and we keep the other frictions at the corresponding levels in the preceding bi-decade. Consequently, we define three counterfactuals as follows: "only$-\omega_\ell$", "only$-\chi, \kappa$", and "only$-\omega_r$". So, for example, when implementing the counterfactual "only$-\omega_\ell$", we use the following set: $\left\{\omega_{j,\ell}^{v_T}, \chi_j^{v_{T-20}}, \kappa_j^{v_{T-20}}, \omega_{j,r}^{v_{T-20}}\right\}$.

The second approach involves feeding the entire calibrated path for only one wedge, while keeping all other wedges unchanged and fixed at their *initial* level in 1860. In contrast to the first approach,

[36] The model also underperforms when we target both the intensive and extensive margins. See the additional results in Figure B3 in Appendix B.

we propagate forward the simulated wealth distributions starting from 1860. This approach is similar to long-run exercises in Aliprantis, Carroll and Young (2022) and Derenoncourt et al. (2024), where frictions are eliminated or simply kept at a specific value while simulating the model over longer time horizons.

5.1 Dynamic Wealth Inequality Accounting and Wedge Contributions

To quantify the individual contribution of each wedge in our model, we use the criterion introduced by Brinca et al. (2016) for the business cycle accounting literature. We define a statistic $\phi^y_{x,t}$ to capture how closely a given wedge x is associated with a particular wealth gap metric y in period t (e.g., the share of households with nonpositive wealth) :

$$\phi^y_{x,v_T} = \frac{1/(y_{v_T} - y_{x,v_T})^2}{\sum_z 1/(y_{v_T} - y_{z,v_T})^2}, \tag{7}$$

where y_{x,v_T} is the counterfactual value of y when only the wedge $x \in \{\omega_\ell; \chi, \kappa; \omega_r\}$ is active in bi-decade v_T, and y_{v_T} is the realized value for outcome y. By construction, when a particular wedge x perfectly tracks the wealth gap metric y, meaning that $(y_{v_T} - y_{x,v_T}) = 0$ in a given bi-decade v_T, then $\phi^y_{x,v_T} = 1$. That is, the ϕ statistic for the wedge reaches its maximum value of 1. In addition, the statistic ϕ^y is defined so that the sum of the individual contributions ϕ^y_i equals 1 at a point in time; that is, $\sum_x \phi^y_{x,v_T} = 1$.

We compute these statistics for the Black-White gap in nonpositive wealth share and the Black-White wealth ratios at the median and top quartile of the positive wealth distribution.[37] The results are summarized in Tables 5, 6, and 7, while the trends are shown in Figure 9.

Nonpositive Wealth Share Gaps. Table 5 shows that the downside risk wedge is the main driver of the extensive margin in our model. In fact, except for the bi-decade 1960 – 1980, when its contribution decreased drastically (panel (a) in Figure 9), the downside risk wedges contributed more than 90% of the racial gap in the share of households with nonpositive wealth. Over the one and a half centuries since Emancipation, labor market frictions and the second layer of capital markets (excess returns) contributed equally and only residually to the left tail differences, at around 7% on average.

[37] For parsimony, we do not report the across-group wealth distribution induced by each wedge in the main text. However, these can be found in Figures C4, C5, and C6 of Appendix C.1.

Table 5: Contribution of Wedges to Racial Gap at the Extensive Margin (%)

	1860 to 1880	1880 to 1900	1900 to 1920	1920 to 1940	1940 to 1960	1960 to 1980	1980 to 2000	2000 to 2020	mean
$\phi^{Shr}_{\omega_\ell,t}$	5.3	0.6	0.1	1.4	3.9	43.6	1.1	2.4	7.3
$\phi^{Shr}_{\chi,\kappa;t}$	90.5	98.8	99.7	97.4	92.6	19.8	98.0	95.4	86.5
$\phi^{Shr}_{\omega_r,t}$	4.1	0.5	0.1	1.2	3.5	36.6	1.0	2.2	6.2

Note: We use Equation 7 to compute the statistic ϕ^{Shr}_{x,v_T}. This metric measures the bi-decadal contribution of wedge x to racial gap in the Black-White gap in nonpositive wealth share in a counterfactual economy where only x is active. The contributions sum to one for each bi-decade v_T, up to rounding errors.

Table 6: Contribution of Wedges to Racial Wealth Gap at the Median (%)

	1860 to 1880	1880 to 1900	1900 to 1920	1920 to 1940	1940 to 1960	1960 to 1980	1980 to 2000	2000 to 2020	mean
$\phi^{p50}_{\omega_\ell}$	99.8	99.4	96.7	93.8	83.3	2.9	37.7	44.9	69.8
$\phi^{p50}_{\chi,\kappa}$	0.1	0.3	1.8	4.2	10.9	96.4	60.1	46.3	27.5
$\phi^{p50}_{\omega_r}$	0.1	0.3	1.4	2.0	5.8	0.7	2.2	8.8	2.7

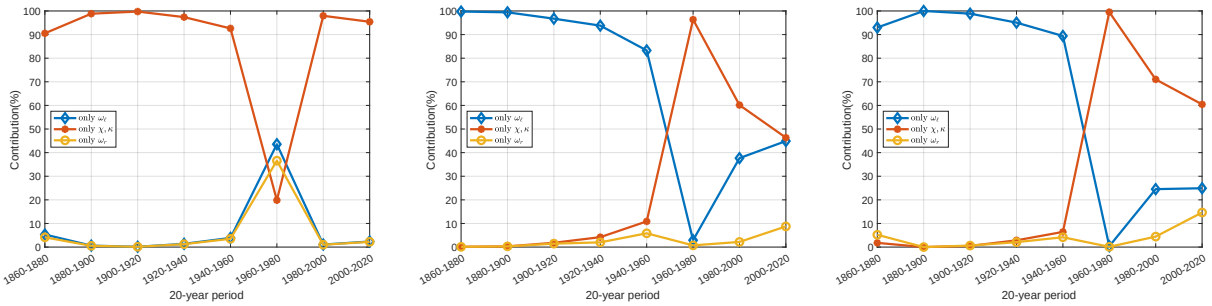
Note: We use Equation 7 to compute the statistic ϕ^{Shr}_{x,v_T}. This metric measures the bi-decadal contribution of wedge x to Black-to-White ratio of median positive wealth in a counterfactual economy where only x is active. The contributions sum to one for each bi-decade, up to rounding errors.

Table 7: Contribution of Wedges to Racial Wealth Gap at the Top Quartile (%)

	1860 to 1880	1880 to 1900	1900 to 1920	1920 to 1940	1940 to 1960	1960 to 1980	1980 to 2000	2000 to 2020	mean
$\phi^{p75}_{\omega_\ell}$	93.0	100.0	98.9	95.1	89.4	0.4	24.5	24.9	65.8
$\phi^{p75}_{\chi,\kappa}$	1.8	0.0	0.5	2.9	6.4	99.5	71.0	60.4	30.3
$\phi^{p75}_{\omega_r}$	5.2	0.0	0.6	2.1	4.2	0.1	4.4	14.6	3.9

Note: We use Equation 7 to compute the statistic ϕ^{Shr}_{x,v_T}. This metric measures the bi-decadal contribution of wedge x to Black-to-White ratio of top quartile positive wealth in a counterfactual economy where only x is active. The contributions sum to one for each bi-decade, up to rounding errors.

Figure 9: Contribution of Wedges to Racial Gaps (%)



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Positive Wealth Percentile Ratios. Looking at positive wealth Black-White percentile ratios, Tables 6 and 7 respectively show almost identical decompositions at the median and at the 75th percentile. From 1860 to 1940, the income wedge was virtually the sole force driving intensive margin racial gaps. However, at the outset of the Civil Rights movement, this changed. At that point, the downside risk began to account for almost two-thirds of the contributions and represented the primary driver of racial gaps at the intensive margin, particularly higher in the wealth distribution (see panels (b) and (c) of Figure 9). The excess return wedge appears to be a residual contributor–its contributions barely exceed 10%–even though its role has markedly edged up in the last bi-decade.

An Inflection Since 1960 – 1980. These accounting exercises indicate that the 1960 – 1980 bi-decade represents an inflection period: the dominant wedges shaping racial wealth gaps sharply switched towards financial frictions across the board, even as the wealth-loss correlation element of downside financial risks vanished. Figure 9 suggests that amid this structural change, the racial wealth convergence gains stemming from earnings convergence in the Civil Rights era were both reduced and short-lived because of financial frictions: downside financial risks became key driving forces behind racial gaps at both extensive and intensive margins while earnings gaps remain flat or widened. This observation is also broadly consistent with the central role Derenoncourt et al. (2024) attribute to racial differences in returns for understanding mean racial wealth differences in recent decades.

5.2 Long-Run Decomposition and Convergence Analysis

In our second decomposition approach, we simulate the model over longer time horizons. We feed a selected wedge's calibrated path while the other wedges are fixed to their initial 1860 values.

For example, to analyze how labor market frictions affect the racial wealth convergence path, we run counterfactual scenarios akin to the "only-ω_ℓ" model: (i) we do not re-initialize the initial wealth distributions, and (ii) we keep the other wedges fixed throughout.

Table 8: Fixed Initial Wedges for Simulations – 1860

Parameters (%)	χ_B	χ_W	κ_B	κ_W	$\omega_{B,r}$	$\omega_{W,r}$
Group-specific wedges						
Scenario A	19.0	9.7	98.2	12.7	45.4	54.6
Common wedges						
Scenario B	9.7	9.7	12.7	12.7	54.6	54.6

Note: We use the bi-decadal sequence of calibrated income wedges shown in Table B1 in both scenarios.

We consider two scenarios for these initial values. In Scenario A, initial racial differences in the other wedges are fixed to their group-specific 1860 values throughout. In Scenario B, we also turn off initial differences for the other wedges, and we use the White group's wedge values for both groups throughout (see Table 8). Hence, Scenario B can be thought of as closing the initial gap between the two groups, without turning it off.

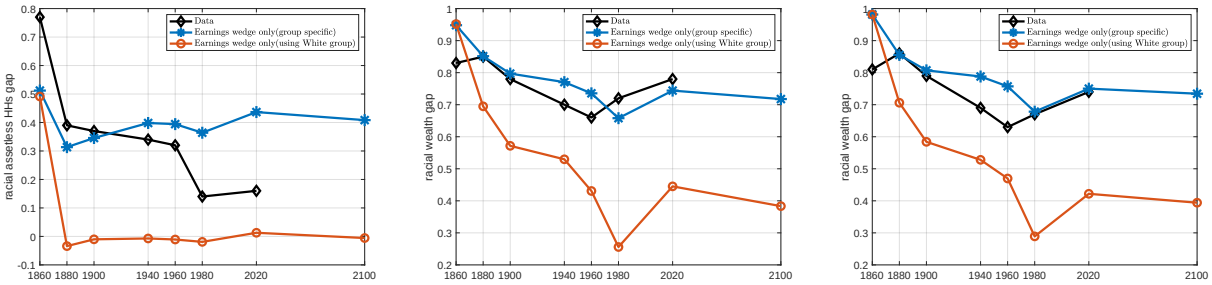
We define the relative intensive margin racial wealth gap for percentiles Pi, $i = \{50, 75\}$, as $\text{RWG}_{\text{P}i} = 1 - \text{Black household wealth}_{\text{P}i} \div \text{White household wealth}_{\text{P}i}$. This relative racial wealth gap decreases as $\text{RWG}_{\text{P}i}$ approaches zero. Figures 10, 11, and 12 show the counterfactual racial wealth gaps using only one wedge at a time.[38] Comparing the results under the two scenarios also highlights the interaction between the dynamics of a given wedge and the initial racial gaps for the other wedges.

Earnings Wedge Dynamics Alone. In Figure 10, with group-specific initial values and active earnings dynamics, the intensive margin dynamics (panels b and c) from 1860 to 2020 are close to the data. This is consistent with income frictions' large contributions to the intensive margin and more persistent wealth destruction probabilities (see Table B1 in Appendix B). At the extensive margin (panel a), under group-specific initial values, the counterfactual exercise implies much less convergence. This too is consistent with downside risk wedges' outsized contribution to extensive margin dynamics.

However, initial gaps also interact with the impact of earnings wedge dynamics. In particular, we

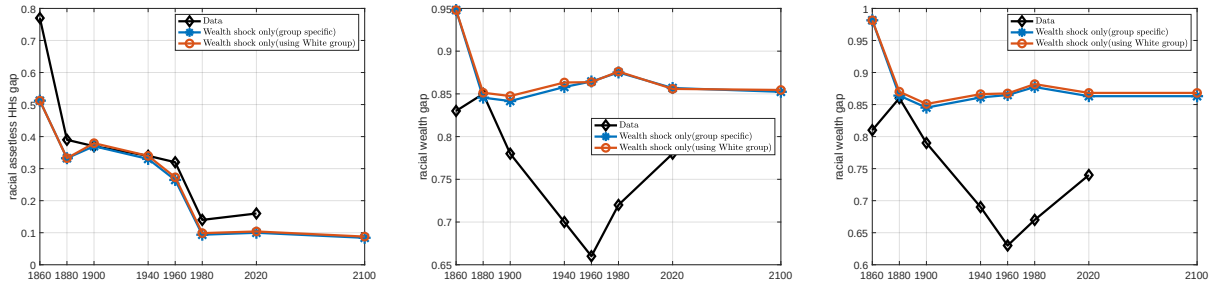
[38] See Figures C7, C8, and C9 in Appendix C.2 for counterfactual gaps when we use the relative wealth ratio instead; that is, $\text{RWG}_{\text{P}i} = \text{Black household wealth}_{\text{P}i} \div \text{White household wealth}_{\text{P}i}$.

Figure 10: Convergence Path with Income Wedge Only



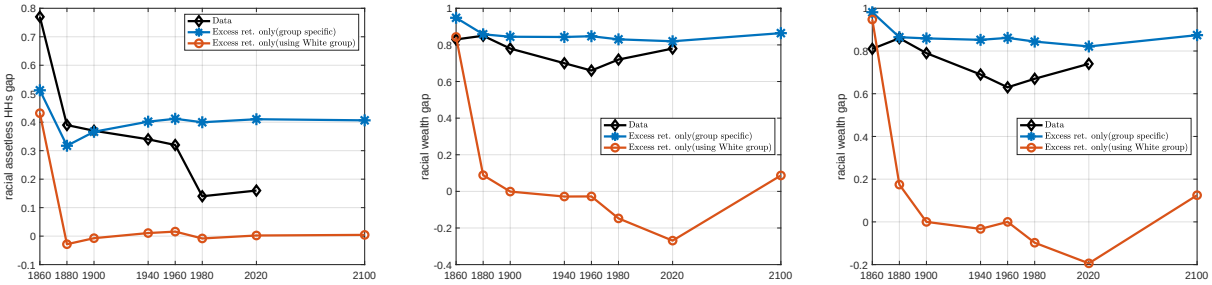
(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 11: Convergence Path with Downside Risk Wedges Only



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 12: Convergence Path with Excess Return Wedge Only



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

observe that an early closing of the financial wedges (Scenario B) leads to more and stronger convergence: extensive margin gaps close right after Emancipation, while intensive margin gaps respond more strongly to earnings convergence during the Civil Rights era. An early elimination of racial wealth downside risk gaps would have stimulated enough Black wealth accession to equalize the left tail of the wealth distribution across groups two decades after Emancipation. The convergence path at the intensive margin is not as dramatic and front-loaded as the extensive margin convergence, even if it is steeper than the group-specific scenario. All told, equalizing financial market frictions at Emancipation would have reduced the racial wealth gaps by 2020 by 40 percentage points across all three metrics.

Looking further out, under downside risk equalization at Emancipation, the Black/White wealth ratio would converge from 1:1.8 in 2020 and 1:1.7 in 2100. This is qualitatively consistent with the simulations in Derenoncourt et al. (2024), where the racial wealth gap would be 1:3 in 2020 and 1:1.4 in 2200, when racial income gaps close in their model.

Downside Risks Dynamics Alone. How would racial wealth gaps have evolved if only wealth downside risks changed over time? Figure 11 answers this question, assuming labor market frictions and the second layer of financial market frictions (excess returns) are kept at initial 1860 levels, either using group-specific or White group values.

The counterfactual with downside risks alone tracks observed extensive margin gaps very well (panel a). However, downside risk wedges alone yield muted and larger racial gaps at the intensive margin (panels b and c), compared with the data. By 2020, the counterfactual racial wealth gap is approximately 10 percentage points higher than in the data. This result confirms that wealth destruction and indebtedness frictions alone explain some but not all the closing of the wealth accumulation gap.

It is also instructive to compare the outcomes under an equalization of earnings at Emancipation (Scenario B). In contrast to the simulations for earnings dynamics alone, it is striking that both experiments yield similar convergence patterns: while downside risks matter, closing earnings gaps early does not materially change the racial wealth implications from group-specific downside risk dynamics alone.

Excess Return Wedge Dynamics Alone. We now turn to counterfactual dynamics of racial wealth gaps when the excess return wedges alone are active. Figure 12 traces the evolution of racial differences at the extensive margin (panel a) and at the intensive margin (panels b and c). As in the two previous

counterfactuals, labor market frictions and the second layer of financial market frictions (downside risks) are kept at initial 1860 levels, using either group-specific or White group values.

Excess return wedges only had a marginal contribution of racial wealth disparities. As a result, when the initial racial differences in earnings and downsides risks are maintained, excess returns alone lead to more persistent racial wealth disparities. On the other hand, when initial wedges are common for both groups, racial excess return wedge dynamics lead to a total closing of racial wealth gaps–even a reversal of the gaps when the excess return is higher for Black households relative to White households.

5.3 Robustness: Are Preferences Instrumental?

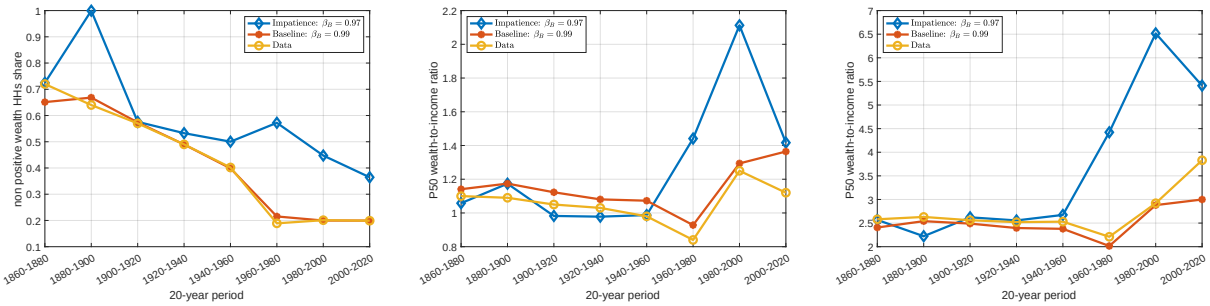
In Section 2, we deliberately assumed that Black and White households share common preferences. Specifically, we argued for and considered both groups to be equally patient and equally risk-averse: they have the same discount factor, β, and the same coefficient of risk aversion, σ. Yet, for completeness' sake, we now revisit our findings under the problematic, but not uncommon, of innate preference heterogeneity *across* groups.[39] As is common among many conventional economists, and following stereotypes prevalent among many 20$^{\text{th}}$ century writers, we now assume that Black households are less patient than White households and also consider that Black households are more risk-averse than their White counterparts.[40]

Aren't Black Households Simply More Impatient? We implement this experiment by setting the discount factor for Black households to $\beta_B = 0.97$, while keeping the discount factor for White households at its baseline value, $\beta_W = 0.99$. Consequently, we recalibrate only the parallel economy for Black households; the economy consisting solely of White households remains unchanged. Figure 13 illustrates how lower patience affects the *recalibrated* model's fit within the Black group, at both the extensive and intensive margins. Additionally, Figure 14 shows the impact of reducing the patience of Black households on non-targeted wealth distribution metrics across groups. Overall, in both figures, the baseline model—with equal discount factors—provides a better fit than the version with more impatient households.

[39] Our guiding principle is symmetry, not homogeneity *per se*. We understand that it is unlikely that any one racial group can be characterized fully by one metric, and that there may be significant differences within a group. See De Nardi and Fella (2017) on the importance of embedding rich demographic heterogeneity in models of wealth inequality.

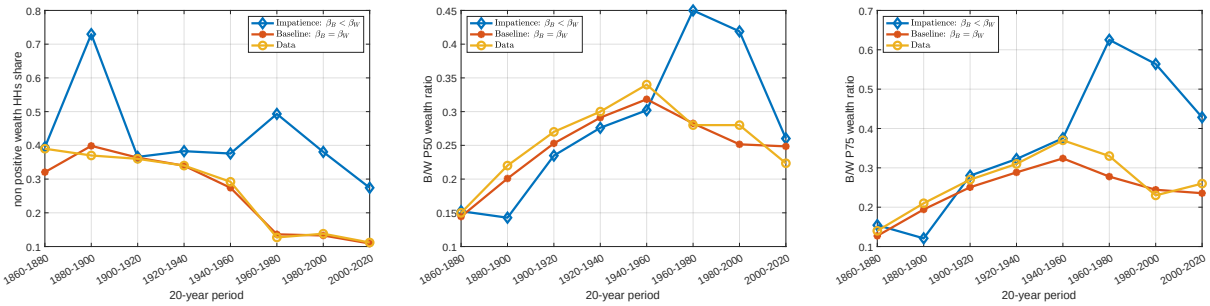
[40] Boerma and Karabarbounis (2023) alternatively suggest an endogenous learning channel in which past exclusions may lead to persistent differences in subjective returns and, thereby, gaps in risk-taking and wealth. See also Andrews et al. (2017) and Albright et al. (2021) on the persistent effects of past racial exclusions or violence.

Figure 13: Impatience and Intragroup Wealth Inequality for Black Households



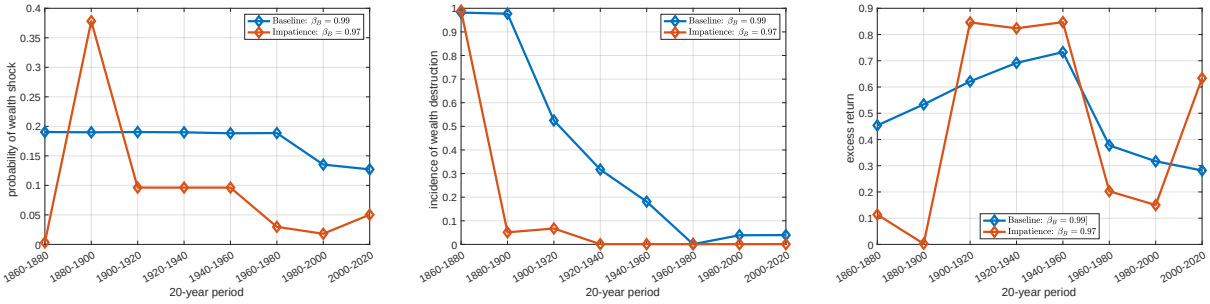
(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 14: Wealth Distributions: Impact of Impatience on Gaps Across Groups



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 15: Impatience and Calibrated Wedges



(a) Wealth destruction probability (b) Wealth-loss correlation (c) Top wealth excess return

Lower patience significantly lowers the propensity to accumulate wealth. As a result, a larger share of households falls into the left tail of the wealth distribution, as shown in panel (a). Furthermore, Figure 15 shows that greater impatience reduces the risk of wealth destruction: the wealth-loss correlation falls to nearly zero earlier than in the baseline scenario. The model recalibrated with more impatience overshoots on the intensive margins of Black wealth after 1960, as downside risks are estimated to fall near zero, below White downside risk values! Taken together, these findings provide strong evidence against the problematic hypothesis that time preference differences trivially explain racial wealth gaps.

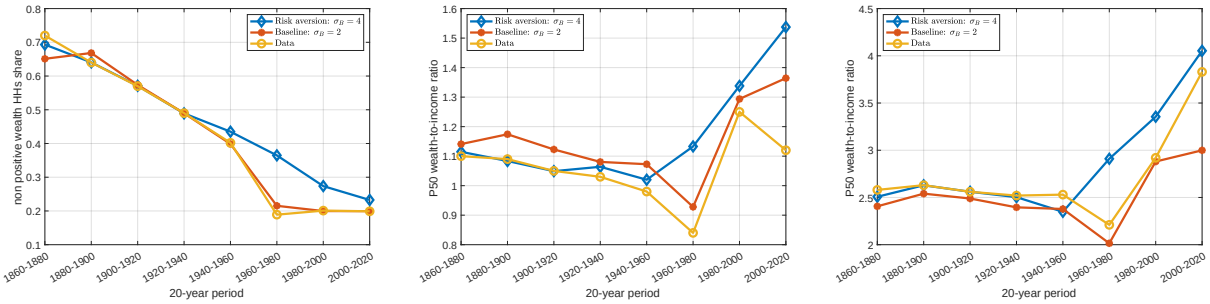
Aren't Black Households Simply More Risk-Averse? Risk attitudes too influence saving behavior. We now turn to the often discussed, yet equally problematic, view that Black households are innately more risk-averse than White households.[41] To this end, we assign a higher risk aversion coefficient to the Black group while keeping the coefficient of the White group at its baseline value. Specifically, we set $\sigma_B = 4$ and $\sigma_W = 2$, and recalibrate only the economy with Black households.

Intragroup wealth distributions are shown in Figure 16. From the earlier decades until the 1940s, the counterfactual scenario with higher risk aversion fits the data about as well as the baseline does. The many episodes of racial violence against Black individuals following Emancipation, combined with the institutionalized Jim Crow environment, may have discouraged Black households from engaging in risky endeavors and from accumulating significant wealth. To be clear, we think a baseline with higher downside risks and similar risk aversion pre-1940 is historically more accurate than the idea that Black households before 1940 were somehow simply more risk-averse. Needless to say, these two alternative views have very different welfare and policy implications.

However, after 1940s, the higher risk aversion counterfactual tends to be less aligned with the data. For example, in panel (a), more households appear in the left tail of the wealth distribution: the alternative model is unable to deliver the decline in zero wealth household gap around the Civil Rights era. In panels (b) and (c), wealth inequality becomes even more pronounced in the right tail also. Figure 17, which depicts the implied wealth distributions between groups, closely mirrors the patterns in Figure 16. Similarly to the impatience scenario, an increase in risk aversion dampens the saving motive in a risky environment. This, in turn, leads the model to require fewer destruction events and results in a smaller stock of wealth being destroyed (see Figure 18).

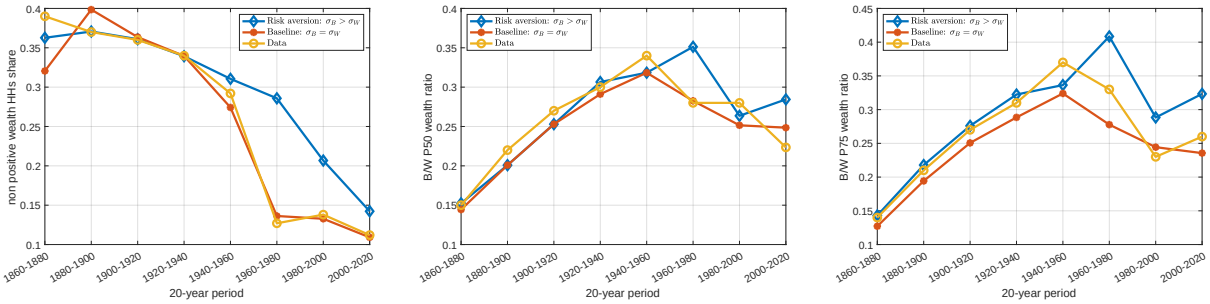
[41] See Myers (1980) for an early investigation of the presumed role of *lower*, not higher, risk aversion among Black people as a driver of Black-White differentials in crime rates.

Figure 16: Risk Aversion and Intragroup Wealth Inequality



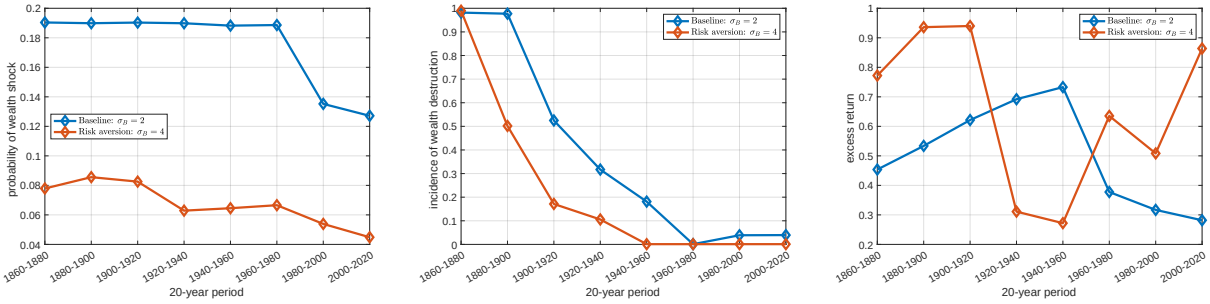
(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 17: Wealth Distributions: Impact of Risk Aversion on Gaps Across Groups



(a) Nonpositive wealth gap (b) Positive wealth P50 ratio (c) Positive wealth P75 ratio

Figure 18: Risk Aversion and Calibrated Wedges



(a) Wealth destruction probability (b) Wealth-loss correlation (c) Top wealth excess return

Overall, the results in this scenario do not support the problematic hypothesis that Black households are innately more risk-averse than their White counterparts.

6 Evidence on Housing Downside Risks in Recent Decades

Are racial gaps in downside risks completely passé? Since racial gaps are large across the wealth distribution, we explore downside risks to the primary wealth source for most households: housing wealth.[42]

6.1 Racial Differences in Homeownership Exit Rates

To study homeownership downside risks, we leverage the panel dimension of the Panel Study of Income Dynamics (PSID) to compute, by period and by race, transition rates from homeownership into renting. For comparison, we also compute transition rates from renting into homeownership. We show these group-and-decade specific exit rates along with homeownership rates, in Figure 19.

We see in panel (a) of Figure 19 that the racial homeownership gap is also large and persistent, as is consistent with the racial wealth gaps at the median. Yet, panel (b) shows that the racial gap in entry rate *into* homeownership has narrowed over time.

In fact, the racial homeownership gap is also shaped by a racial homeownership *exit* gap. Panel (c) reveals that exit rates *out of* homeownership are significantly larger and have been rising for Black homeowners, even as homeownership exit rates have been weakly declining for White homeowners. Furthermore, Figure 20 shows larger estimated residualized exit rates for Black households and suggest Black homeowners may face larger downside risks.[43]

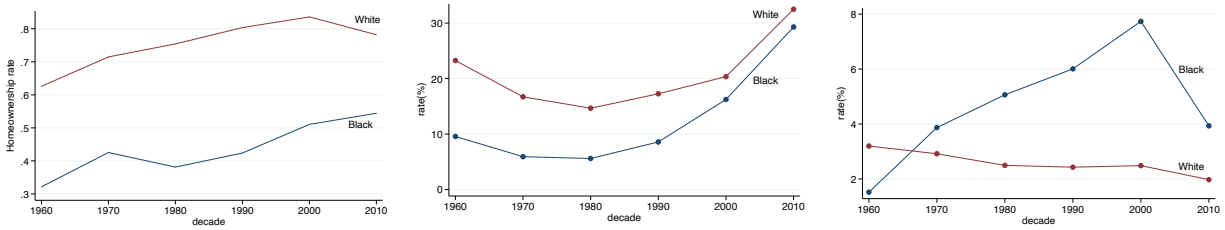
6.2 Property Loss, Insurance, and Race

We further focus on downside risks by investigating racial differences in how insured homeowners recover losses from natural hazards: a more direct test of racial differences in downside risks.

[42] Charles and Hurst (2002) study the credit market determinants of racial homeownership gaps. Kermani and Wong (2024) also document lower realized returns from distressed home sales by Black and Hispanic households in the 2000s, compared with the returns received by White households. Taylor (2019) argues that risk and race are systemically tied in America's history of housing segregation: first through exclusion and redlining, and later through "predatory inclusion."

[43] Myers et al. (2023) leverage the longitudinal dimension of the Health and Retirement Survey (HRS) to document significant racial gaps in the accumulation of both housing and non-housing wealth among older Americans. See Figure D10 in the appendix for conditional homeownership exit rates in the HRS.

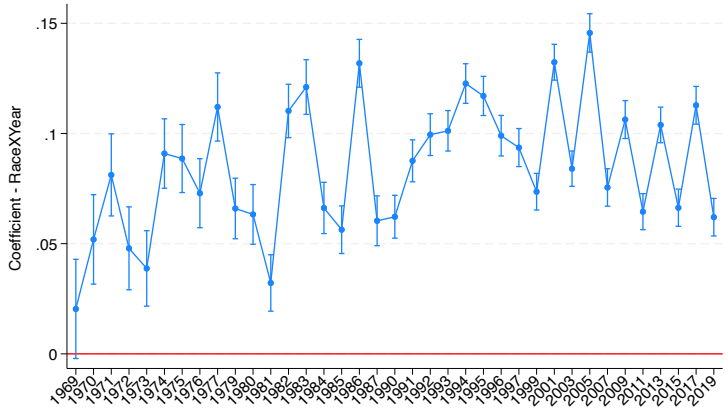
Figure 19: Homeownership Rates and Flows by Race (PSID)



(a) Homeownership (b) Entry (c) Exit

Note: Average of yearly rates across years by race within a decade. Source: PSID (1968-2019).

Figure 20: Conditional Homeownership Exit Rates for Black Homeowners (PSID)



Note: Race-year fixed effects after controlling for income, home value, property taxes, marital status, and region. Source: PSID (1968-2019).

Federal Homeowners' Insurance 2018–2022 Data. We leverage an extensive survey of the homeowners insurance market commissioned by the Federal Insurance Office (FIO), part of the U.S. Department of the Treasury (Federal Insurance Office, 2025). The report made available comprehensive ZIP code-level annual data from 2018 to 2022 on homeowners' insurance, based on over 330 insurers on more than 246 million homeowners insurance policies across 33,000 populated residential ZIP Codes. The data are based on the Property & Casualty Market Intelligence (PCMI) Data Call sent to homeowners' insurers. The FIO ZIP-level data focus on multi-peril insurance for owner-occupied properties on two primary policy forms, "Special Form" HO-3 and "Comprehensive Form" HO-5, which account for almost 85% of the homeowners' insurance market (Federal Insurance Office, 2025).[44]

We use the following variables available in the FIO PCMI dataset for location i and year t: (i) the insurer's "Paid Loss Ratio" $\ell_{i,t}$ – the ratio of amounts paid on claims to or on behalf of policyholders relative to premiums received, (ii) the "Claim Frequency" $f_{i,t}$ – the percentage of claims insurers have paid relative to the policies issued, (iii) the "Policy Premium" $p_{i,t}$ – the average cost of a policy, and (iv) the "Claim Severity" $c_{i,t}$ – the average amount of each claim paid by the insurer.

The SHELDUS Data on Natural Hazard Events We combine the FIO PCMI data with county-level yearly data on natural hazard events and associated property damages from SHELDUS (CEMHS, 2025). SHELDUS is a county-level hazard data set for the U.S. and covers, from 1960 to present, natural hazards, such as thunderstorms, hurricanes, floods, wildfires, and tornadoes, as well as perils such as flash floods, heavy rainfall, and so on. It contains information on the date of an event, affected location (county and state), and the direct losses caused by the event.[45] These data allow us to isolate shocks to the claims frequency (deviations from expected claims) and to estimate how these claims on passed to the homeowner or to the insurer through higher paid loss ratios. See Tables E3 and E4 in Appendix E for summary statistics on the resulting dataset.

Hazard Events, Claims, and Insurer Losses By construction, $\ell_{i,t} \equiv f_{i,t} \times c_{i,t} \div p_{i,t}$. We investigate Black-White differences in the elasticity of insurer losses to claim frequencies, a measure of insulation from downside risks. More claims (f) mechanically shift insurer losses (ℓ) upward. However, it is

[44] The data were collected via the National Association of Insurance Commissioners (NAIC) and state regulators.

[45] See Gall, Borden and Cutter (2009) and Ash, Cutter and Emrich (2013) on the quality of the SHELDUS data and their limitations, including potential biases in the composition of hazards.

unclear how other drivers of insurer losses respond. To fix ideas, let us consider unexpected increases in claim frequencies $f_{k,t}$ and $f_{j,t}$, following natural hazard events at two locations k and j at time t. Differentiating with respect to claim frequencies and taking differences across locations yields

$$\left[\frac{\mathrm{d}\log \ell_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log \ell_{j,t}}{\mathrm{d}\log f_{j,t}}\right] = \left[\frac{\mathrm{d}\log c_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log c_{j,t}}{\mathrm{d}\log f_{j,t}}\right] - \left[\frac{\mathrm{d}\log p_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log p_{j,t}}{\mathrm{d}\log f_{j,t}}\right]. \tag{8}$$

We see that when the insurer approves and pays claims of less severity, the insurer loss ratio will be lower. More importantly, differences across locations k and j in this claim severity $\left(\frac{\mathrm{d}\log c_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log c_{j,t}}{\mathrm{d}\log f_{j,t}}\right)$ elasticity govern differences in the insurer losses elasticity across locations $\left(\frac{\mathrm{d}\log \ell_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log \ell_{j,t}}{\mathrm{d}\log f_{j,t}}\right)$. Needless to say, the premium too can rise in response to claim frequency increases and thereby offset or lower insurer losses. We conjecture that this premium elasticity $\left(\frac{\mathrm{d}\log p_{k,t}}{\mathrm{d}\log f_{k,t}} - \frac{\mathrm{d}\log p_{j,t}}{\mathrm{d}\log f_{j,t}}\right)$ is likely small.

We leverage the SHELDUS data on natural hazard events to find exogenous incidence or exposure shocks that lead to insurer-approved increases in claims $f_{i,t}$. We then estimate the elasticity of insurer losses to claims and ask whether homeowners in areas with more Black residents have a lower insurer loss elasticity and more downside risk.[46]

Racial Gaps in Insurer Losses on Claims from Natural Hazard Events. To isolate racial gaps in the elasticity of insurer losses to claims due to natural hazards, we estimate the following fixed-effect two-stage least squares equation for outcomes $y \in \{\ell, c, p\}$:

$$\begin{aligned}\Delta \log y_{i,t} = \quad & \beta^{y}\ \widehat{\Delta \log f_{i,t}} \\ & + \beta^{y}_{\text{Black}}\ \widehat{\Delta \log f_{i,t}} \times \widehat{\text{share Black}}_{i,2010} \\ & + \beta^{y}_{\text{Poor}}\ \widehat{\Delta \log f_{i,t}} \times \widehat{\text{share Poor}}_{i,2010} + \mu^{y}_{i} + \delta^{y}_{t},\end{aligned} \tag{9}$$

where i is a county, $t = 2018, \ldots, 2022$, μ^{y}_{i} location fixed effects, and δ^{y}_{t} year fixed effects. Given secular changes in climate and insurance pricing (Federal Insurance Office, 2025), location fixed effects capture location-specific trends. Local poverty share effects control for the correlation of race and income.[47]

The term $\widehat{\Delta \log f_{i,t}}$ denotes the instrumented change in (log) claim frequency $\Delta \log f_{i,t}$. Specifically,

[46] See Logan and Parman (2017) on the evolution of racial residential segregation and Bayer et al. (2022) on neighborhood-level segregation dynamics.

[47] We use county or tract characteristics from Opportunity Insights, and the HUD ZIP-TRACT and ZIP-COUNTY crosswalks. We use the 2000 and 2010 Census H1 ZIP level housing units counts to weight the aggregation of FIO PCMI data from ZIP to county. We restrict our sample to ZIP codes with claim frequencies and insurer loss ratios in [0,1].

we use as instruments the change in (log) per capita property damage value from natural hazard events in SHELDUS and the lagged value of (log) claims. We instrument the 2010 Census shares of Black residents (share Black$_{i,2010}$) and residents below the poverty line (share Poor$_{i,2010}$) using the 2000 Census values. We illustrate this first stage in Figure E11 and the reduced form of β^{ℓ} in Figure E12 across bins of share Black$_{i,2010}$ in Appendix E.

Racial Gap Estimation Results. We report our estimation results in Table 9 for the OLS and the IV 2SLS specifications implemented using the `xtivreg2` STATA package.[48]

First, we find that shocks to homeowners' insurance claims arising from natural hazards lead to significantly higher losses (IV $\beta^{\ell} = +0.76$) for the insurers, and that these losses are moderated by lower claim severity (IV $\beta^{c} = -0.17$). We find no significant offsetting effect from changes in premium.

Table 9: Insurer Losses and Homeowners Claims Following Natural Hazard Events

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.83***	0.76***	–0.13***	–0.17***	–0.00	0.01*
	(0.036)	(0.046)	(0.037)	(0.046)	(0.007)	(0.007)
$\Delta \log f_{i,t} \times$ share Black$_{i,2010}$	–0.36***	–0.35***	–0.43***	–0.39***	–0.01	0.04**
	(0.094)	(0.115)	(0.097)	(0.116)	(0.018)	(0.017)
$\Delta \log f_{i,t} \times$ share Poor$_{i,2010}$	–0.11	0.07	0.06	0.03	0.03	–0.09**
	(0.234)	(0.294)	(0.244)	(0.297)	(0.045)	(0.044)
N (county-year)	12,136	8,684	12,136	8,684	12,136	8,684
Number of counties	3,075	2,907	3,075	2,907	3,075	2,907
R-Sq	0.415	0.427	0.048	0.049	0.006	0.009
Cragg-Donald Wald F statistic	–	534.46	–	534.46	–	534.46

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and PCMI data from Federal Insurance Office (2025).

Note that the elasticity of insurer losses to claim frequency is theoretically equal to 1 if claim severity or premia do not adjust. In general, $\beta^{\ell} = 1 + \beta^{c} - \beta^{p}$, since $\Delta \log \ell_{i,t} = \Delta \log f_{i,t} + \Delta \log c_{i,t} - \Delta \log p_{i,t}$. In fact, $1 + \beta^{c} = 0.83 \approx 0.76 \pm .046 = \beta^{\ell}$.[49]

However, the insurer loss elasticity to claims is significantly more muted in areas with more Black

[48] The OLS estimates hold using a ZIP-code level fixed-effect regression, but the hazard data are at the county level.

[49] The FIO PCMI data also contain information on *nonpayment cancellation rates*, the share of policies canceled before the policy period ends because policyholders failed to pay, as well as *nonrenewal rates*, the share of policies insurers did not renew when the policy period ends due to the risk profiles. Changes in both cancellation rates and nonrenewal rates are not correlated with hazard-driven changes in claim frequencies.

residents (IV $\beta^{\ell}_{\text{Black}} = -0.35$). This lower insurer loss elasticity is due to larger claim severity declines (IV $\beta^{c}_{\text{Black}} = -0.39$). These results suggest that Black homeowners still face more severe housing wealth downside risks, compared with White homeowners.[50]

Housing Risks, Insurance, and Race Black households have long faced predatory and discriminatory practices on the journey to own and keep their homes (Taylor, 2019).[51] After the 1960s uprisings, Black-populated urban areas were denied hazard coverage and left without private insurance options. The Fair Access to Insurance Requirements (FAIR) plans perpetuated a racially tiered system by providing "back of the bus" insurance (Ansfield, 2021). Eventually, when FAIR defined "arson-prone" areas, it set off a nationwide urban arson wave by absentee landlords and speculators: up to 80% of the housing stock in parts of the Bronx were lost in arson by the late 1970s (Ansfield, 2021, pg. 920). Casey and Hardy (2018) use tract-level data to suggest economic outcomes were worse in Black neighborhoods more directly exposed to the 1960s riots.

7 Conclusion

The slow, glacial pace of racial wealth convergence since the end of Reconstruction makes Black Americans' wealth accumulation journey seem like a Sisyphean endeavor. We propose a parsimonious model to consistently unpack the dynamic drivers of observed racial wealth disparities in the U.S. since 1860.

We uncover a significant role for wealth accumulation frictions modeled as downside risks, over and above conventional labor market earnings frictions. Racial gaps in these wealth downside risks also appear to be negatively correlated with racial gaps in earnings: the Civil Rights era saw both more rapid racial convergence in earnings and greater racial divergence in downside wealth risks – perhaps due to the racially segregated dynamics of urban decline, White suburban flight, or rising Black incarceration.

We find that disparities and dynamics at the left tail of the wealth distribution are essential for understanding the frictions that shape the fortunes, or lack thereof, of Black and White households in America. Even though the model is highly stylized, it illustrates how plausible and enduring wealth accumulation frictions shape racial wealth disparities.

[50] In Appendix E, Tables E5–E7 show the results are concentrated in places with a large share of Black residents, and Tables E8–E10 show the results are driven by smaller counties.

[51] See Squires (1997) on insurance redlining and Heen (2009) on the history of race-based practices in life insurance.

Our results on the presence of significant downside wealth risks along with the evidence on its plausible markers also imply that policy designs need to be robust to frictions that manifest as greater financial fragility. These findings echo recent contributions on the salience of the nexus of race and financial frictions or risks in America (Maroto and Sykes, 2020; Kermani and Wong, 2024; Derenoncourt et al., 2024; Argyle et al., 2025; Humphries et al., 2025; Feir, Jones and Redish, 2024; Bakker et al., 2025) as well as new explorations of capital market responses to racial justice demands in America (Jenkins, 2023; Taylor, 2019; Ba, Rivera and Whitefield, 2023).

Above all, our accounting approach points to the types of models needed to understand the evolution of racial wealth disparities: models with wedges manifesting as downside risks to wealth are a promising direction for understanding both the fragility of wealth and its persistence, especially with respect to race and ethnicity. A natural next step for future research is to incorporate these wealth downside risks using evidence over the life cycle, across generations, or across racially segregated spaces into richer models of wealth accumulation (Charles and Hurst, 2003; De Nardi, 2004; Kaplan and Violante, 2014; Athreya et al., 2025).

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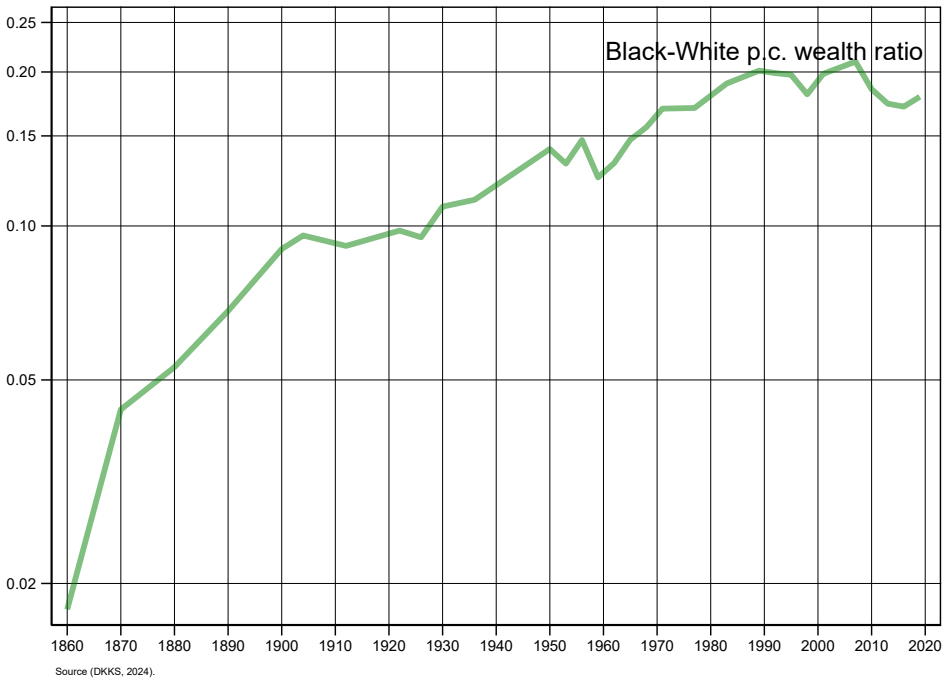
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Online Appendix

A Relative Black-Wealth Mean Wealth

Figure A1: Black-Wealth Mean Wealth Ratio



Note: Mean Black per capital wealth divided by mean White per capita wealth over time using a log scale the y-axis. Source: Authors' calculations using Derenoncourt et al. (2023, 2024) and Kuhn, Schularick and Steins (2020) replication datasets.

B Additional Calibration Results

Table B1: Calibrated Wedges

Wedge	1860	1880	1900	1920	1940	1960	1980	2000
				to				
(by group, in %)	1880	1900	1920	1940	1960	1980	2000	2020
				Earnings wedge				
$\omega_{B,\ell}$	71.0	69.0	60.0	53.0	44.0	24.0	48.0	43.0
$\omega_{W,\ell}$	–	–	–	–	–	–	–	–
				Downside risk wedge				
χ_B	19.0	19.0	19.0	19.0	18.8	18.9	13.5	12.7
χ_W	9.7	12.2	12.4	12.0	11.9	6.7	6.2	6.5
κ_B	98.2	97.7	52.5	31.2	18.1	0.1	3.9	3.9
κ_W	12.7	9.7	5.9	2.0	0.2	0.1	0.1	2.0
				Excess return wedge				
$\omega_{B,r}$	45.4	53.4	62.1	69.2	73.3	37.8	31.7	28.2
$\omega_{W,r}$	54.6	84.0	90.6	69.0	94.8	5.9	3.4	70.9
				Expected Wealth Tax				
$\tilde{\chi_B}$	37.0	36.8	28.6	24.8	22.1	18.9	14.0	13.2
$\tilde{\chi_W}$	10.9	13.4	13.1	12.3	11.9	6.7	6.2	6.6

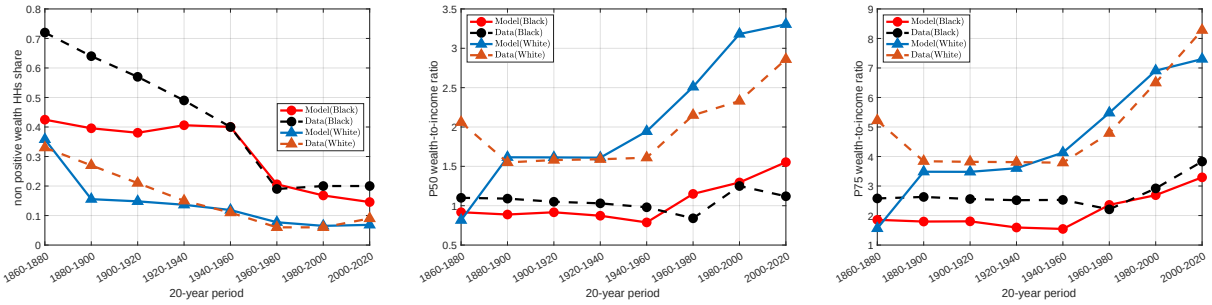
Note: We normalize $\omega_{W,\ell} = 0$. All parameters are in percentage points.

Table B2: Calibrated Wealth Taxes

Wedge gaps	1860	1880	1900	1920	1940	1960	1980	2000
				to				
(B – W, in %)	1880	1900	1920	1940	1960	1980	2000	2020
$\tau_{B,a}$	14.4	13.10	12.7	12.7	12.7	12.7	12.7	12.7
$\tau_{W,a}$	9.5	9.6	9.4	9.6	11.0	9.6	9.6	8.1

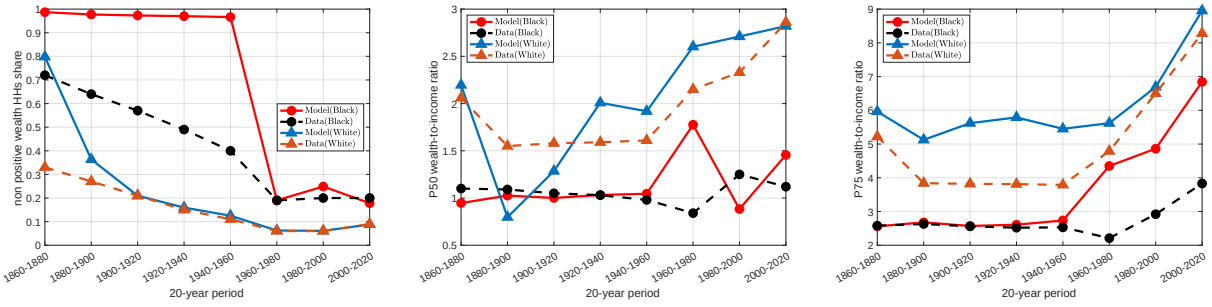
Note: All parameters are in percentages. For the sake of exposition, we do not report the other calibrated wedges in this table.

Figure B2: Extensive and Intensive Margins Without Wealth-Loss Correlation



(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

Figure B3: Extensive and Intensive Margins with Wealth Tax



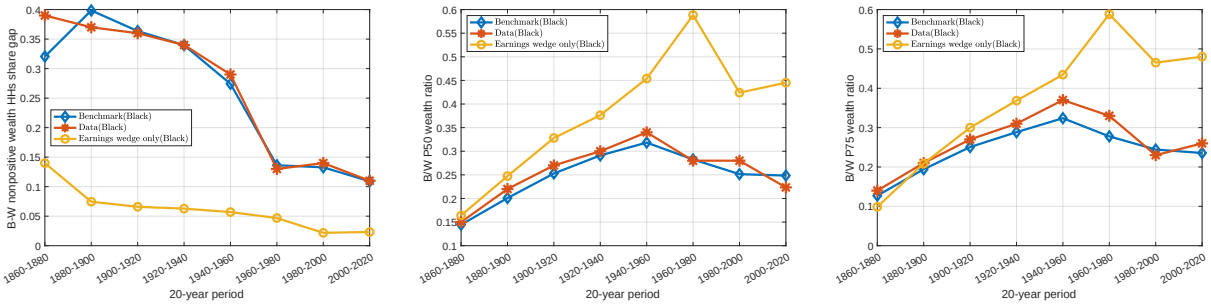
(a) Nonpositive wealth share (b) P50 positive wealth-to-income (c) P75 positive wealth-to-income

C Additional Results From Counterfactual Exercises

C.1 Bi-Decadal Contributions of the Wedges: Additional Results

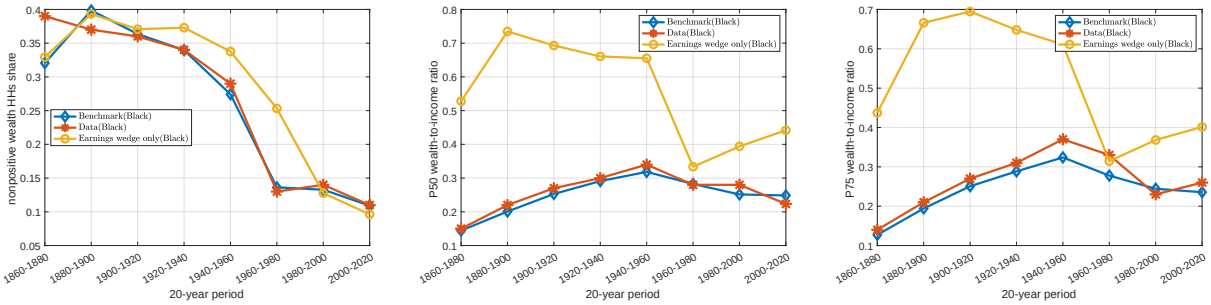
In this section, we present the racial wealth gap at the extensive margin and at the intensive margins using alternative assumptions on the paths of the wedges by activating the income wedge only, the downside risk only, or the top wealth excess return wedge only.

Figure C4: Wealth Distributions Across Groups: Only Income Wedge



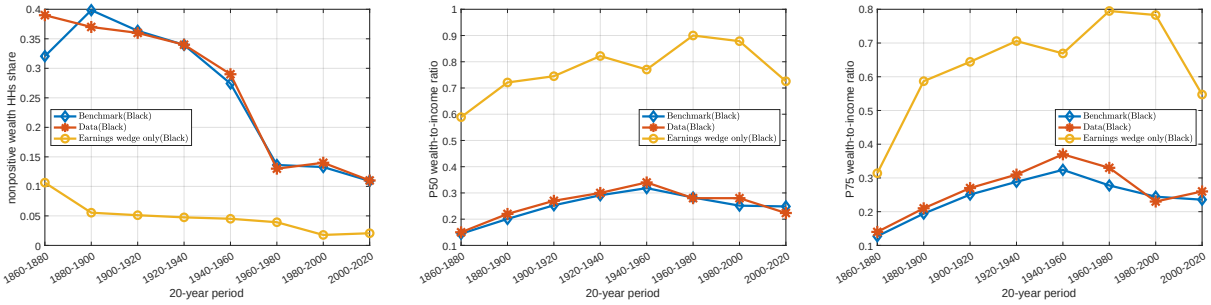
(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

Figure C5: Wealth Distributions Across Groups: Only Downside Risk



(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

Figure C6: Wealth Distributions Across Groups: Only Excess Returns Wedge



(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

C.2 Long-Run Decomposition and Convergence: Additional Results

The figures in this section present the racial wealth gap at the intensive margins by using the ratio of the respective percentiles. Specifically, in Section 5.2, we define the racial wealth gap (RWG) as follows:

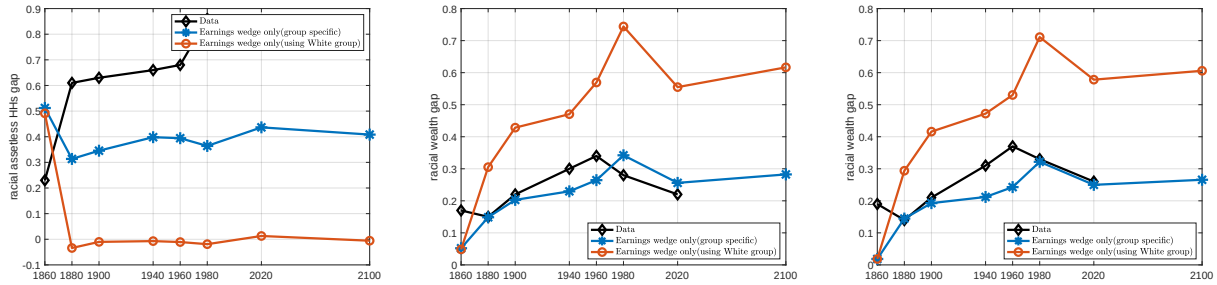
$$RWG_{Pi} = 1 - \frac{\text{Black household wealth}_{Pi}}{\text{White household wealth}_{Pi}}, i = \{50, 75\}.$$

Thus, the racial wealth gap decreases as RWG_{Pi} approaches zero. However, if we define the racial wealth gap in absolute terms, we use the following formula:

$$RWG_{Pi} = \frac{\text{Black household wealth}_{Pi}}{\text{White household wealth}_{Pi}}, i = \{50, 75\}.$$

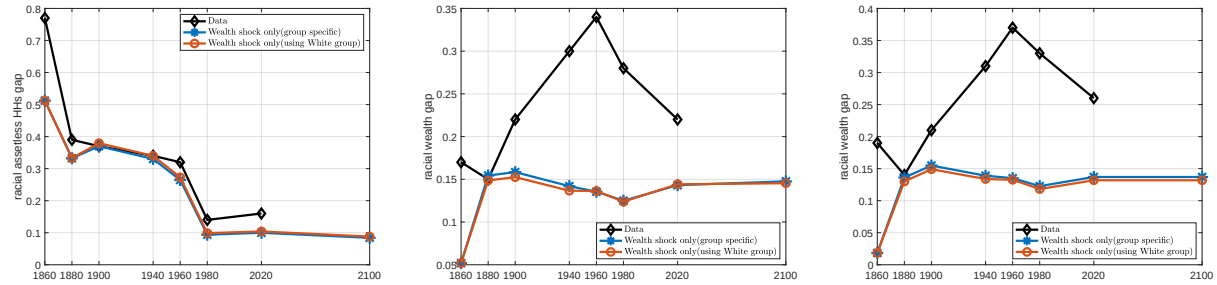
In this case, a higher RWG_{Pi} indicates more convergence between the two groups.

Figure C7: Convergence Path with Income Wedge Only



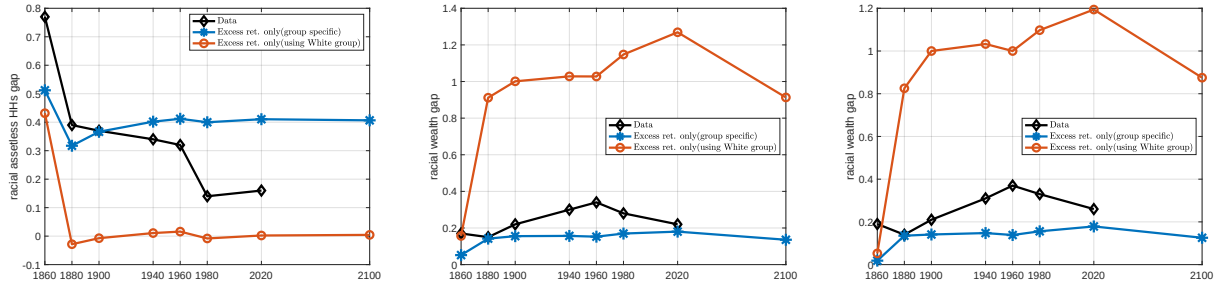
(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

Figure C8: Convergence Path with Downside Risk Wedges Only



(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

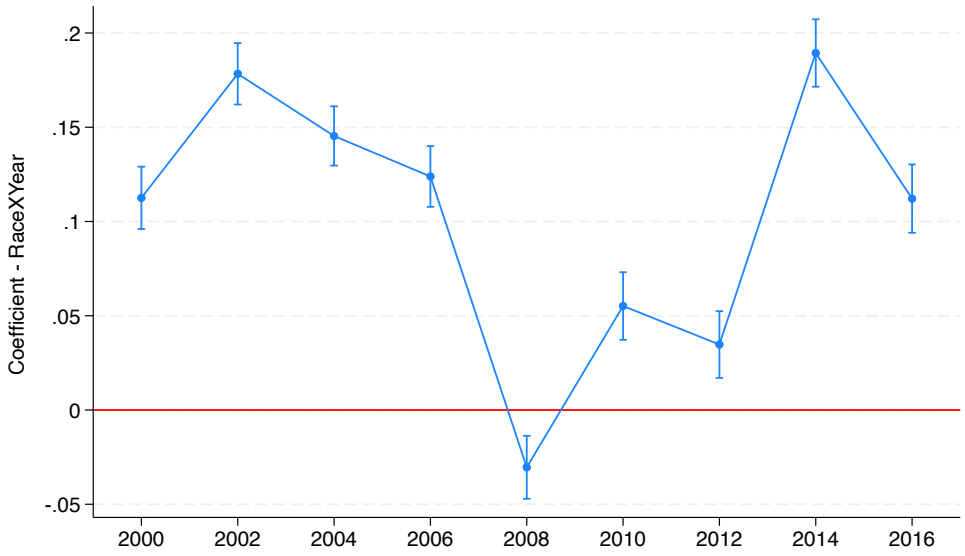
Figure C9: Convergence Path with Excess Returns Wedge Only



(a) Nonpositive wealth gap (b) Positive wealth p50 ratio (c) Positive wealth p75 ratio

D Homeownership Exit Rates in the HRS

Figure D10: Conditional Homeownership Exit Rates for Black Homeowners in the HRS



Note: We report race-year fixed effects and control for retirement income, supplemental income, net house value, and region. Source: HRS (1992-2018).

E FIO PCMI Insurance Data Appendix

Table E3: County-Level FIO PCMI Summary Statistics

Black pop. share	variable	N	mean	P90	std. dev.
Total	Premium	12,136	1,707.69	2,402.82	734.69
	Claim Severity	12,136	15,044.35	22,288.42	7,432.38
	Claim Frequency	12,136	0.05	0.08	0.03
	Insurer Loss Ratio	12,136	0.37	0.59	0.16
	Positive Property Damage	12,136	0.69	1	0.46
	Property Damage per HU	11,688	1,995.47	77.98	107,980.38
	Housing Units HU	12,136	39,772.89	84,491	115,268.91
	2010 Share Pop. Poor	12,136	0.16	0.24	0.06
	2010 Share Pop. Black	12,136	0.09	0.31	0.15

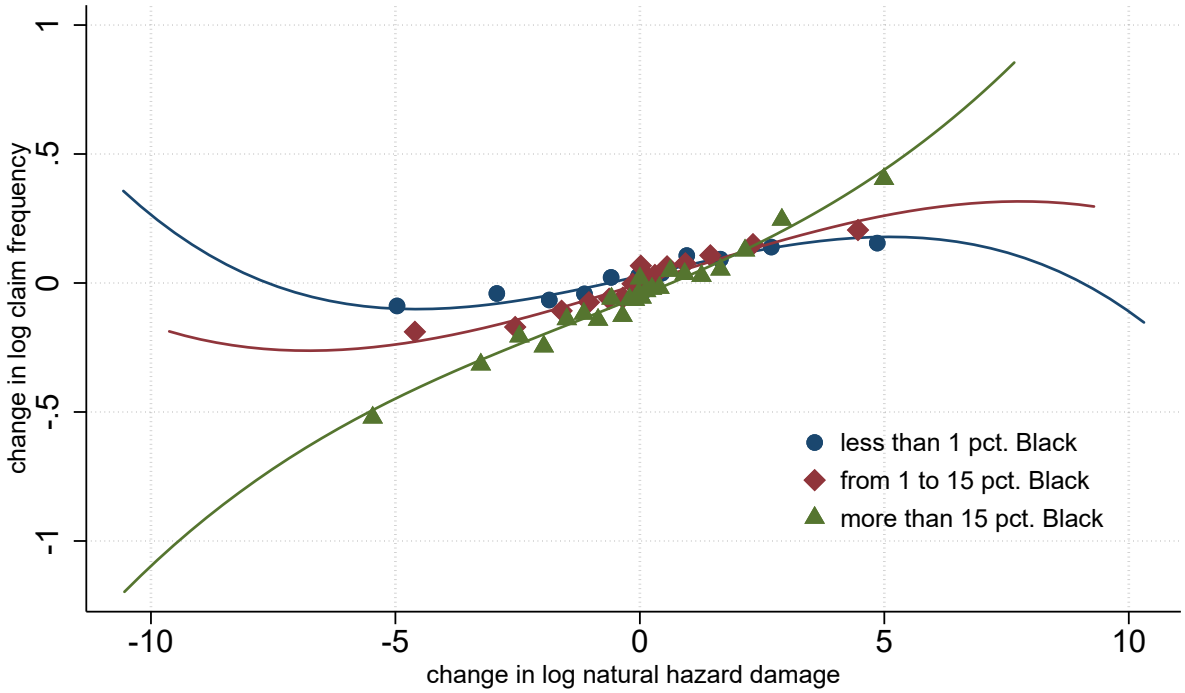
Note: Summary statistics are provided for the sample used in the baseline OLS regressions. N refers to the number of county-year observations. Claim severity and Premium are inflation-adjusted by the FIO. Property damage values are in 2022 dollars. Source: SHELDUS^{TM} 23 from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E4: County-Level FIO PCMI Summary Statistics by Black Population Share

Black pop. share	variable	N	mean	P90	std. dev.
$\leq$ 1 pct	Premium	4,039	1,638.91	2,311.80	546.43
	Claim Severity	4,039	15,206.02	24,399.82	8,961.56
	Claim Frequency	4,039	0.04	0.07	0.03
	Insurer Loss Ratio	4,039	0.33	0.56	0.17
	Positive Property Damage	4,039	0.60	1	0.49
	Property Damage per HU	3,777	1,324.86	106.87	26,971.77
	Housing Units HU	4,039	9,423.28	19,996	15,440.22
	2010 Share Pop. Poor	4,039	0.14	0.22	0.06
	2010 Share Pop. Black	4,039	0.01	0.01	0.00
1 to 15 pct	Premium	5,658	1,720.70	2,481.96	845.57
	Claim Severity	5,658	15,553.48	22,099.50	6,980.95
	Claim Frequency	5,658	0.05	0.08	0.02
	Insurer Loss Ratio	5,658	0.38	0.58	0.15
	Positive Property Damage	5,658	0.73	1	0.45
	Property Damage per HU	5,512	2,702.32	55.01	154,272.72
	Housing Units HU	5,658	51,312.13	114,004	129,466.32
	2010 Share Pop. Poor	5,658	0.15	0.21	0.05
	2010 Share Pop. Black	5,658	0.05	0.11	0.04
$\geq$ 15 pct	Premium	2,439	1,791.41	2,294.01	719.60
	Claim Severity	2,439	13,595.53	18,877.88	5,110.41
	Claim Frequency	2,439	0.06	0.10	0.03
	Insurer Loss Ratio	2,439	0.41	0.64	0.16
	Positive Property Damage	2,439	0.77	1	0.42
	Property Damage per HU	2,399	1,427.21	91.97	31,326.48
	Housing Units HU	2,439	63,263.28	166,566	156,398.43
	2010 Share Pop. Poor	2,439	0.20	0.29	0.07
	2010 Share Pop. Black	2,439	0.34	0.57	0.15

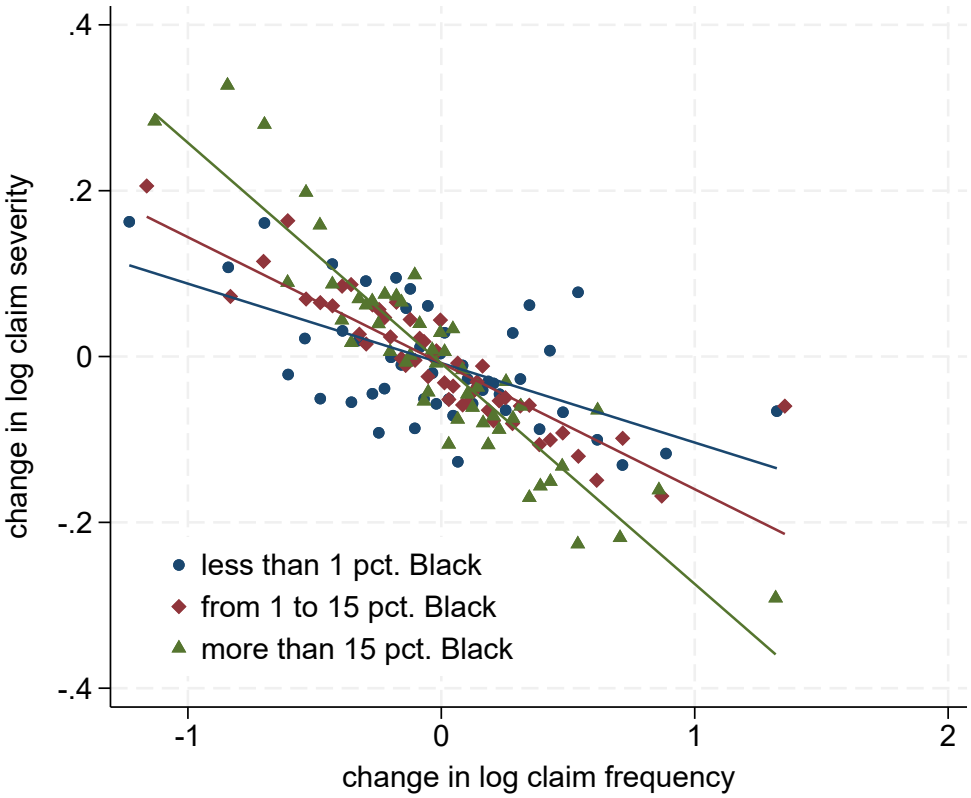
Note: Summary statistics are provided for the sample used in the baseline OLS regressions. N refers to the number of county-year observations. Claim severity and Premium are inflation-adjusted by the FIO. Property damage values are in 2022 dollars. Source: SHELDUS^{TM} 23 from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Figure E11: Illustrating the First Stage



Note: Plot using the `binreg` command and a cubic polynomial fit for three groups of counties based on the share of Black residents. Source: SHELDUS^{TM} 23 from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Figure E12: Illustrating the Elasticity of Claim Severity to Claim Frequency



Note: Plot using the `binreg` command for three groups of counties based on the share of Black residents. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E5: Insurer Losses and Homeowners Claims – share Black$_{i,2010} \in [0, 0.01)$

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.83***	0.81***	–0.10***	–0.13***	0.01	–0.00
	(0.026)	(0.032)	(0.027)	(0.033)	(0.007)	(0.006)
N (county-year)	4,039	2,798	4,039	2,798	4,039	2,798
Number of counties	1,030	940	1,030	940	1,030	940
R-Sq	0.389	0.402	0.027	0.032	0.007	.005
Cragg-Donald Wald F statistic	–	922.25	–	922.25	–	922.25

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E6: Insurer Losses and Homeowners Claims – share Black$_{i,2010} \in [0.01, 0.15)$

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.79***	0.73***	–0.15***	–0.21***	0.00	0.00**
	(0.025)	(0.020)	(0.025)	(0.020)	(0.003)	(0.002)
N (county-year)	5,658	4,114	5,658	4,114	5,658	4,114
Number of counties	1,424	1,374	1,424	1,374	1,424	1,374
R-Sq	0.448	0.451	0.059	0.069	0.021	0.022
Cragg-Donald Wald F statistic	–	1712.61	–	1712.61	–	1712.61

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E7: Insurer Losses and Homeowners Claims – share Black$_{i,2010} \in [0.15, 1)$

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.68***	0.66***	–0.27***	–0.29***	0.00	0.00
	(0.023)	(0.027)	(0.023)	(0.027)	(0.003)	(0.004)
N (county-year)	2,439	1,772	2,439	1,772	2,439	1,772
Number of counties	621	593	621	593	621	593
R-Sq	0.433	0.467	0.119	0.093	0.019	0.019
Cragg-Donald Wald F statistic	–	895.34	–	895.34	–	895.34

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E8: Insurer Losses and Homeowners Claims – Small Counties

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.91***	0.87***	–0.05	–0.06	–0.00	0.02
	(0.048)	(0.078)	(0.051)	(0.080)	(0.009)	(0.012)
$\Delta \log f_{i,t} \times$ share Black$_{i,2010}$	–0.35***	–0.40**	–0.43***	–0.44**	–0.03	0.04
	(0.132)	(0.197)	(0.136)	(0.201)	(0.023)	(0.030)
$\Delta \log f_{i,t} \times$ share Poor$_{i,2010}$	–0.30	–0.23	–0.07	–0.33	0.06	–0.13*
	(0.300)	(0.487)	(0.316)	(0.497)	(0.059)	(0.074)
N (county-year)	5,587	3,700	5,587	3,700	5,587	3,700
Number of counties	1,596	1,255	1,596	1,255	1,596	1,255
R-Sq	0.398	0.407	0.028	0.029	0.007	0.004
Cragg-Donald Wald F statistic	–	213.79	–	213.79	–	213.79

Note: Counties with housing unit count less than 10,000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E9: Insurer Losses and Homeowners Claims– Medium Counties

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.60***	0.68***	–0.38***	–0.30***	–0.02**	–0.01
	(0.047)	(0.048)	(0.043)	(0.049)	(0.007)	(0.008)
$\Delta \log f_{i,t} \times$ share Black$_{i,2010}$	–0.04	0.04	–0.07	-0.00	0.02	0.05*
	(0.109)	(0.144)	(0.106)	(0.146)	(0.020)	(0.025)
$\Delta \log f_{i,t} \times$ share Poor$_{i,2010}$	0.11	–0.81**	0.31	–0.62*	0.05	0.03
	(0.314)	(0.346)	(0.294)	(0.352)	(0.045)	(0.061)
N (county-year)	1,917	1,409	1,917	1,409	1,917	1,409
Number of counties	507	486	507	486	507	486
R-Sq	0.633	0.668	0.417	0.437	0.043	0.062
Cragg-Donald Wald F statistic	–	180.97	–	180.97	–	180.97

Note: Counties with housing unit count between 10,000 and 50,000.Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

Table E10: Insurer Losses and Homeowners Claims – Large Counties

	Insurer Loss Ratio $\Delta \log \ell_{i,t}$		Paid Claim Severity $\Delta \log c_{i,t}$		Insurance Premium $\Delta \log p_{i,t}$	
	(a)	(i)	(b)	(ii)	(c)	(iii)
claim frequency	OLS	IV	OLS	IV	OLS	IV
$\Delta \log f_{i,t}$	0.71***	0.77***	–0.21***	–0.16**	0.00	0.01*
	(0.051)	(0.069)	(0.050)	(0.067)	(0.006)	(0.007)
$\Delta \log f_{i,t} \times$ share Black$_{i,2010}$	–0.03	0.15	–0.09	0.13	0.03*	0.04***
	(0.139)	(0.167)	(0.140)	(0.161)	(0.017)	(0.016)
$\Delta \log f_{i,t} \times$ share Poor$_{i,2010}$	–0.07	–0.56	–0.11	–0.60	–0.07	–0.12***
	(0.400)	(0.436)	(0.398)	(0.422)	(0.048)	(0.041)
N (county-year)	4,632	3,310	4,632	3,310	4,632	3,310
Number of counties	1,291	1,162	1,291	1,162	1,291	1,162
R-Sq	0.460	0.476	0.120	0.108	0.036	0.042
Cragg-Donald Wald F statistic	–	222.08	–	222.08	–	222.08

Note: Counties with housing unit count above 50,000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. These standard errors are clustered at the county level in the OLS regression. Source: SHELDUS from CEMHS (2025) and FIO PCMI data from Federal Insurance Office (2025).

F Measurements and Calibration

F.1 Moments for Income and Wealth Distributions

For each available year, using the SCF+, we compute the following moments.

1. Distributional facts by groups
    - median and mean of non capital income for each group
    - fraction with zero or negative wealth for each group
    - percentiles (P25, P50, P75, P90) of positive (net) wealth holdings for each group
        - We focus on median positive wealth to mean earnings, the p90 over p75 ratio for positive wealth, and the fraction of positive net wealth households.
    - percentiles (p50) of overall (net) wealth holdings for each group
        - We keep track of this moment for reporting–not calibration and simulation–purposes.
2. Implied facts on racial disparities
    - Black-over-White ratio of p50 of non capital income
    - Black-over-White ratio of p50 of net positive wealth
    - Black-minus-White excess fraction of non positive (net) wealth households

Variables Our measure of total household (non-capital) income in the data is the household income from wages, salaries, and from self-employment variable ("*incwsse*" in the SCF+). We exclude observations with negative income. This measure of income therefore combines differences in employment rates, wage rates, and self-employment income between Black and White households. Our measure of household wealth in the data is the household net worth variable ("*ffanw*" in SCF+). We define White households as households with a head who identified as White and non-Hispanic. Black households are households with a head who identified as Black.

F.2 Fitting the Initial Wealth Distribution

Let $Y \in [-\underline{y}, +\infty)$ be a random variable representing the wealth distribution, with $\underline{y} > 0$.

Assumption 1 (Mixture assumption). *We assume*

$$Y = \begin{cases} U & \textit{w.p. } m_0, \\ \tilde{V} & \textit{w.p. } (1 - m_W) \times (1 - m_0), \\ W & \textit{w.p. } m_W \times (1 - m_0), \end{cases} \tag{10}$$

where Y has a CDF F such that

$$U \in [-\underline{y}, 0] \textit{ with CDF } H(u),$$
$$\tilde{V} \in (0, y_W) \textit{ with CDF } \tilde{G}(v),$$
$$W \in [(y_W, \infty) \textit{ with CDF } K(w).$$

Corollary 1 (Mixture CDF). *Y has a CDF F such that*

$$F(y) = \begin{cases} m_0 \times H(y) & \textit{if } y \in (-\underline{y}, 0], \\ (1 - m_W) \times (1 - m_0) \times \tilde{G}(y) & \textit{if } \in (0, y_W), \\ m_W \times (1 - m_0) \times K(y) & \textit{if } y \in (y_W, \infty). \end{cases} \tag{11}$$

Assumption 2 (Truncated log normal $\tilde{G}$). *We assume $\tilde{V}$ follows a truncated Log-normal distribution with CDF $\tilde{G}$ such that:*

$$\tilde{G}(v) = \Pr\left(V \leq v \mid V \in (0, y_W]\right) = \frac{G(v)}{G(y_W)} \qquad \forall\, v \in (0, y_W)\,, \tag{12}$$

where V is a Log-normal distribution $\mathcal{LN}(\mu_a^V, \sigma_a^V)$ over $[0, +\infty)$ and with CDF G.

Assumption 3 (Pareto distribution K). *We assume W follows a Pareto distribution with parameters $[y_W, \alpha_a)$ over $[y_W, +\infty)$ such that the CDF K satisfies*

$$K(w) = 1 - \left(\frac{w}{y_W}\right)^{\alpha_a} \qquad \forall\, w \in [y_W, \infty)\,.$$

Calibrating μ_a^V and σ_a^V Here, we note that $\mathbb{Q}_{a>0}(1-m_W) = y_W$ and that for any $p < 1-m_W$, $\mathbb{Q}_{a>0}(p) = Q_G(p)$.

For any $p, q \leq 1-m_W, \sigma_a$ solves

$$\mathbb{R}_{\sigma_a}(p,q) = \left(\exp\left[\textbf{erf}^{-1}(2p-1) - \textbf{erf}^{-1}(2q-1) \right] \right)^{\sigma_a\sqrt{2}} = r(p,q). \tag{13}$$

In particular, we can set $1-m_W = 0.5, p = 0.5, q = 0.25$. By setting $1-m_W = 0.5$, we can also choose μ_a to solve the median of the lognormal component:

$$\begin{aligned} y_W &= \mathbb{Q}_{Y \mid a>0}[p = 0.5] \\ &= \mathbb{Q}_{Y \mid a>0 \,\&\, a<y_W}[p = 0.5] \\ &= \mathbb{Q}_V[p = 0.5] \\ &= \exp(\mu_a). \end{aligned}$$

That is,

$$\mu_a = \ln y_W. \tag{14}$$

Note that we can work on $a \equiv$ a in the data/mean earnings.

Calibrating α_a For any $p > (1-m_W)$,

$$\mathbb{Q}_{a>0}[p] = Q_K[p-(1-m_W)] = y_W\Big[1-p+(1-m_W)\Big]^{-\frac{1}{\alpha_a}}. \tag{15}$$

For any $p, q \leq 1-m_W, \alpha_a$ solves

$$\mathbb{R}_{\alpha_a}(p,q) = \left\{ \frac{\Big[1-p+(1-m_W)\Big]}{\Big[1-q+(1-m_W)\Big]} \right\}^{-\frac{1}{\alpha_a}} = r_K(p,q). \tag{16}$$

In particular, we can set $1 - m_W = 0.5, p = 0.9, q = 0.75$. We then choose α_a to solve the quantile ratio of the Pareto component:

$$r_K(p,q) = \mathbb{R}_{\alpha_a}(p,q) = \left\{ \frac{\left[1 - 0.9 + (0.5)\right]}{\left[1 - 0.75 + (0.5)\right]} \right\}^{-\frac{1}{\alpha_a}},$$

$$\alpha_a = \ln \left\{ \frac{\left[1 - 0.75 + (0.5)\right]}{\left[1 - 0.9 + (0.5)\right]} \right\} \Big/ \ln r_K(p,q).$$