Rising Income Risk at the Top*

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Abstract

We document an increase in U.S. income risk from 1969 to 2019 using newly digitized IRS tax returns, distinguishing permanent from transitory risk. Since the 1970s, permanent income risk increased across the distribution, but most sharply among high earners, rising nearly 70% among the top 5%. We show that, even among top earners, large negative income shocks strongly predict financial distress and higher income risk is linked with higher savings. In a quantitative life-cycle model, rising income risk concentrated at the top lowers the risk-free rate by 0.7pp, increases wealth inequality, and contributes to the "savings glut of the rich."

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Recently, there has been substantial debate over the evolution of income risk in the United States, with some studies arguing that income risk likely declined in administrative data on individual earnings (e.g., Guvenen et al. (2022), Salgado et al. (2023)), while others have found stable or rising income risk using alternate methods and data sources (e.g., Moffitt et al. (2022), Ziliak et al. (2022)). In this paper, we revisit this question using a newly available panel of household income from the universe of U.S. 1040 tax returns spanning 1969 to the present. These data allow us to measure income at the household level, including business income, and to track its evolution across the entire income distribution over a long horizon. We use these data to address two questions: *How has income risk evolved over time and across the income distribution?* and *What are the aggregate consequences of these changes?* We find that income risk has risen for all households and especially high-income households since 1969, both in near-raw data and in our estimated income process. We then study the macroeconomic implications of these changes by nesting our income process in a quantitative Bewley-Huggett-Aiyagari model. We show that rising income risk at the top of the distribution increases savings among high-income households, lowers the risk-free rate, and contributes to the expansion of wealth inequality.

In this paper, we make four contributions. Our first contribution is to empirically document the evolution of income risk across the income distribution and over time. To motivate this exercise, we start by computing the variance of income changes over 5 and 10-year horizons in the (near) raw tax data. We document three main facts. First, the variance of 5-year income changes has been largely flat since 1969, while the variance of 10-year income changes has increased substantially. Because longer-horizon income changes primarily reflect shocks to permanent income, these patterns suggest that permanent income risk has increased over the past 50 years, while transitory risk has remained flat or declined. Second, across the income distribution, the variance of both 5- and 10-year income changes is asymmetrically U-shaped: risk declines from the bottom through roughly the 80th percentile and then rises sharply at the top of the distribution.[1] Third, we move beyond existing studies and show that these increases in longer-horizon income risk are concentrated among top earners, with the variance of 10-year income changes increasing by nearly 15% at the 95th percentile of the prior income distribution since the 1970s and nearly 40% for the top 1 percent.

Motivated by these results, we then write down a permanent-transitory income process where the variance of shocks to permanent and transitory income is allowed to vary by decade as well as by lagged income rank. We estimate our income process using the approach of Braxton et al. (2025) which allows for estimating a rich income process that makes the parameters a

[1] These cross-sectional patterns align with the variance of 1-year and 5-year income differences in Guvenen et al. (2014) and Guvenen et al. (2021), which are estimated on individual W2 earnings.

function of observables (in our context, lagged income rank and time) and recovers estimates of permanent and transitory income for every person in every period via the Kalman filter. Crucially, the fact that an individual's risk profile depends on lagged income significantly fattens the right tail of the income distribution and adds higher-order income risk. Our parameter estimates reveal two main results. First, permanent income risk is asymmetrically U-shaped with permanent income risk increasing sharply as we move into the right tail of the distribution, a feature we refer to as *convex permanent income risk*. Second, we show that permanent income risk has increased substantially at the top of the income distribution. For the top 5% of households it has increased, on average, by 70% and for the top 1% it has effectively doubled since the 1970s. Our baseline results utilize adjusted gross income less interest and dividend income, and we show that our results are robust to many alternative measures, including considering only wage and salary income. We also document that these patterns hold within both self-employed and non-self-employed individuals.

Our second contribution is to validate that households at the top of the income distribution do in fact face risk. For this exercise, we show that our recovered permanent income shocks (via the Kalman filtering step in our estimation) among high-income households are correlated with observable signals of economic distress. In particular, we find that in response to a 1-SD decline in permanent income, households are more likely to: (1) have an early 401(k) withdrawal and (2) move to a ZIP code with a 30% lower median income. Importantly for each of these results, we show that these patterns of responding to a permanent income shock hold within the top 1% of the income distribution.[2] Thus, we view these results as validating that high-income households do in fact face a substantial amount of income risk.

Our third contribution is to empirically measure how these changes in risk impact savings behavior. We build on Smith et al. (2023) and capitalize interest and dividend income to build proxies for wealth and savings rates. We then measure how savings-to-income ratios respond to within-income rank and across-occupation variation in income risk.[3] Conditional on income rank, we find that savings-to-income ratios rise by 4.7% of prior income for a 0.1 increase in the variance of permanent income shocks (i.e., permanent income risk). We find much smaller savings responses to increases in transitory income risk. Further, we show that the increase in

[2] In a companion paper (Braxton et al. (2025)), we show large declines in permanent income are associated with large increases in the likelihood of filing for bankruptcy, entering foreclosure, and recording a debt charge-off, even among individuals in the top 2% of the income distribution.

[3] Our empirical approach of exploiting occupation level variation in permanent risk to elicit a savings response follows a long tradition in the precautionary savings literature (e.g., Carroll and Samwick (1997) and Boar (2021), and references therein). Relative to these papers, we compare differences across occupations but within income rank. We additionally examine the heterogeneity in the savings response to income risk across the income and age distribution. Our finding that younger households have a larger savings response to permanent income risk aligns with the "buffer stock" theory of savings (e.g., Carroll (1997)).

savings in response to permanent risk is concentrated among younger and high-income households. We refer to these moments as *savings elasticities* and use them to validate our quantitative model.

Finally, our fourth contribution is to quantitatively examine how both convex and rising income risk affect savings at the top, wealth inequality, and interest rates. To do so, we embed our income process into a finite life-cycle Bewley–Huggett–Aiyagari-style model in which households face idiosyncratic income shocks that depend on their lagged income rank and can self-insure by saving and borrowing in a risk-free asset. We calibrate the model to match moments from the distribution of asset-to-income ratios among young households, as well as the evolution of asset-to-income ratios over the life-cycle. We then validate the model by showing that it reproduces our empirical savings elasticities: in particular, that high-income households substantially increase their saving in response to increases in permanent income risk.

We first use the quantitative model to evaluate the degree to which convex permanent income risk drives saving behavior among high-income households. The baseline model generates the empirical pattern that saving rates increase steeply across the income distribution, consistent with the evidence shown in Carroll (2000), Dynan et al. (2004), Straub (2019), and Mian et al. (2020), among others. We then show that, in a version of the model where permanent income risk is flattened above the 95th percentile (effectively removing the convexity at the top), saving rates among rich households decline substantially relative to the baseline model. This decline in saving among the rich also lowers wealth concentration. Thus, the convexity of permanent income risk that we estimate plays an important role in accounting for both the high saving rates of the rich and the concentration of wealth at the top.

Having established that the convexity of permanent income risk is quantitatively important for saving behavior at the top, we then ask how the observed changes in income risk since the 1970s affect aggregate outcomes in general equilibrium. Using the model as a laboratory, we find that changes in income risk since the 1970s raise the top 1% wealth share by 5.1 percentage points. Increased saving by top earners also lowers the risk-free rate from 3.5% to 2.8%, and the resulting decline in interest rates further magnifies wealth inequality. The economic logic is straightforward. In partial equilibrium, an increase in income risk raises precautionary saving demand throughout the income distribution. In general equilibrium, however, the additional demand for assets pushes down the risk-free rate, dampening saving incentives. For most households, especially those below the 90th percentile of the earnings distribution, declining returns to saving more than offset greater precautionary motives, causing saving rates to fall. Among top earners, in contrast, the rise in income risk is sufficiently large that precautionary motives dominate the equilibrium decline in interest rates, leading their saving rates to increase sharply. The model therefore generates a central feature of the data emphasized by Mian et al. (2020): a "savings glut of the rich," in which saving rises at the top even as it falls for the rest of the distribution.

To isolate the role of changes in income risk among top earners, we conduct a narrower counterfactual in which only the estimated income process for households at or above the 95th percentile are allowed to change between the 1970s and 2010s. For all households below the 95th percentile, the income process is held fixed at its 1970s level. Changes in income risk among this narrow group account for about one-quarter of the model's predicted decline in the risk-free rate and nearly all of the increase in the top 1% and top 0.1% wealth shares.

We then gauge the magnitude of the model's predictions by measuring the share of the observed increase in wealth inequality and decline in interest rates that the model explains. Based on the SCF+, the wealth share of the top 1% increased by 11.5 percentage points between the 1970s and 2010s. Rising income risk generates a 5.1 percentage point increase in top 1% wealth shares over the same time window, explaining 44.3% of the data. Rising income risk among the top earners alone (at or above the 95th income percentile) explains 39.7% of the increase in top 1% wealth shares. In terms of interest rates, updated time series from Laubach and Williams (2003) shows that real rates, which we proxy with "R-star," fell by 2.5 percentage points between the 1970s and 2010s.[4] Rising income risk generates a 0.7 percentage point decrease in the risk-free rate, explaining 27.7% of the data. Rising income risk among the top earners alone (at or above the 95th income percentile) explains 6.9% of the decline in the risk-free rate in the data. Taken together, these results suggest that greater risk of top earners played a central role in rising wealth concentration and a moderate role in declining interest rates, while the broader-based increase in risk played a substantial role in declining interest rates.

Literature. This paper relates to several recent literatures. First, we contribute to work studying the evolution of income risk in the U.S. (e.g., Guvenen et al. (2022), Salgado et al. (2023), Moffitt et al. (2022), Ziliak et al. (2022), as well as Braxton et al. (2025) and references therein). Relative to this literature, we measure income risk using administrative data on household income and incorporate business income into the estimation. We show that although the variance of 5-year income changes has been largely flat to declining since the 1970s, the variance of 10-year income changes has steadily increased. These differences across horizons provide evidence that permanent income risk has risen. We further show that these increases have been concentrated among high-income households, especially at longer horizons.

We also speak to the literature estimating non-linear income processes (e.g., Arellano et al.

[4] Alternate time series, including the Federal Reserve Bank of Cleveland's 10-year real rate and the total return on wealth (Auclert et al., 2021) yield similar benchmarks.

(2017), De Nardi et al. (2020), Guvenen et al. (2021), Almuzara et al. (2025), and references therein). Relative to these papers, we examine how income risk varies both *across* the income distribution and *over* time. Our estimation reveals that permanent income risk rises sharply in the right tail of the income distribution, a feature we refer to as *convex* permanent income risk. We also show that permanent income risk has increased substantially among high-income households since the 1970s. To assess whether these estimated shocks capture genuine risk, we show that large declines in permanent income among high-income households are followed by early 401(k) withdrawals and moves to lower-income neighborhoods. The fact that these responses persist within the top 1% provides evidence that even households at the top of the income distribution face meaningful permanent income risk.

The paper then connects these findings to the literature studying the decline in U.S. interest rates over the past 40 years. Existing explanations emphasize several forces, including increasing income inequality (e.g., Favilukis (2013), Kaymak and Poschke (2016), Auclert and Rognlie (2018), Aladangady et al. (2021), Mian et al. (2021a), and Mian et al. (2021b), among others) and changing financial and demographic factors (e.g., Caballero et al. (2008), Favilukis (2013), Caballero et al. (2017), Farhi and Gourio (2018), Auclert et al. (2021)). Relative to these papers, we study how changes in income risk affect aggregate saving and equilibrium interest rates, with particular emphasis on the fact that rising risk has been especially pronounced among high-income households. We discipline this mechanism using an identified moment, in the spirit of Nakamura and Steinsson (2018), that links exposure to greater permanent income risk to household saving behavior.

Our paper further contributes to the literature studying the evolution and drivers of wealth inequality (e.g., Saez and Zucman (2016), Hubmer et al. (2021), Moll et al. (2022), Smith et al. (2023), Gomez (2023), Irie (2026), and references therein).[5] Many of these papers emphasize forces that act disproportionately on entrepreneurs and other high-income individuals whose earnings are closely tied to firm profits—forces that, in turn, generate rising income risk at the top of the income distribution.[6] Our contribution is to measure this risk directly, using detailed panel tax records and a flexible income process, and to quantify its consequences for saving, interest rates, and wealth inequality.[7] To gauge the strength of this channel, we build

[5] A related literature has examined the modifications and channels needed to get quantitative Bewley models to be consistent with the data on top wealth inequality. Recent papers in this literature include De Nardi and Fella (2017), Gaillard et al. (2023), and Hubmer et al. (2026). We show that the convexity of permanent income risk at the top of the lagged income distribution contributes to the high degree of wealth concentration.

[6] Relatedly, Gomez and Gouin-Bonenfant (2024) illustrate a channel through which lower rates directly contribute to rising wealth inequality.

[7] Further, we estimate our income process separately for both workers and the self-employed / entrepreneurs and examine the evolution of income risk for each of these groups.

on Saez and Zucman (2016) and Smith et al. (2023) to capitalize interest and dividend income and construct proxies for saving.

A related literature examines whether high-income households save more than lower-income households and why (e.g., Carroll (2000), Dynan et al. (2004), Straub (2019), Fagereng et al. (2019), Mian et al. (2021b), and references therein).[8] We contribute to this literature by showing that convex permanent income risk gives high-income households a stronger motive to save. More broadly, the income process we estimate shares features with the stylized model of income dynamics with a superstar income state proposed by Castaneda et al. (2003). Unlike the estimated 4-point Markov chain in Castaneda et al. (2003) which exhibits a high degree of mean reversion (20% chance of exiting the superstar state annually), the highest earners in our model expect positive continued earnings growth.[9] High-income households also face substantially greater permanent income risk than other households, and this risk has grown over time. Our paper therefore provides a channel for why high-income households have traditionally saved more throughout the life cycle and why their saving has increased over the past 50 years: they face higher and rising permanent income risk.

The paper proceeds as follows. We begin by discussing our panel of household income from 1040 tax returns and use the data to provide a series of motivating facts in Section 1. We detail the econometric income process in Section 2. We then present our estimation results in Section 3. We use those estimates to discipline our quantitative model in Section 4 and measure the effects of rising risk on interest rates and wealth inequality in Section 5. Lastly, we conclude in Section 6.

1 Data and Motivation

Before describing our income process estimation and quantitative modeling, we provide an overview of our dataset and motivating facts for our analysis.

1.1 Data

Our analysis is based on new linkages between tax data and surveys. Our primary dataset is a panel of 1040 tax returns that starts in 1969 and is available every five years through 2019, i.e., we are able to observe an individual in our panel in years that end with 4 or 9 (1969, 1974, ...,

[8] Additionally, there is a long tradition of examining how saving and wealth behavior respond to changes in risk in quantitative models, e.g., Carroll (1997) and Gourinchas and Parker (2002).

[9] Despite assuming a random walk in permanent earnings, we entertain flexible drift coefficients and therefore flexible mean-reversion. The permanent income drift among p100 agents is still positive (Figure 16).

2014, 2019). In the 1040s, we are able to observe whether an individual has a spouse (and after 1994 if they have dependents), the household level of adjusted gross income (AGI), wage and salary income (WSI) as well as interest and dividend income.[10]

Our baseline income measure is adjusted gross income (AGI) net of interest and dividend income. This definition of income includes wage and salary income as well as business income.[11] We show in Appendix C.2 that our results are robust to using alternative definitions of income such as adjusted gross income (AGI) and wage and salary income (WSI). Central to this paper is the ability to observe interest and dividend income, which we can use to create a capitalized measure of wealth. By tracking how capitalized wealth evolves over time, we can examine how households respond to changes in income risk.[12]

While we have access to the full universe of 1040s, our baseline sample comprises the 1040s for individuals who are in the Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS).[13] The ASEC asks questions that provide additional labor market information that is not readily available on tax forms (e.g., occupation, education, self-employment status) that will allow us to further understand the drivers of income risk across the distribution as well as how households respond to changes in risk. We link individuals from the ASEC to their income information in the tax panel using unique identifiers called Protected Identification Keys (PIKs). We show in Appendix C.3 that our results for the trends in the evolution of income risk across the income distribution are robust to using a random sample of 1040s.

Our measures of income (e.g., AGI, interest and dividend income, etc.) are reported at the household level but the data is constructed so that we have a panel of individuals. To avoid double counting incomes for households with multiple adults, we give each adult a weight of one-half in a two-adult household. Note that since our baseline sample is comprised of individuals in the ASEC, we additionally use sampling weights from the ASEC. As we discuss in more detail below, we remove changes in household composition as part of our residualization process. Thus, we think of our sample construction as sampling individuals to measure household outcomes.

[10] See Alexander, Bleckley, Fisher, Genadek, Leonard, and Magganas (2024) for information on the construction of the 1040 panel.

[11] Data on interest income is available starting in 1969 in our sample, while data on dividend income is available starting in 1974. We infer the level of dividend income in 1969 by taking the ratio of dividend income to AGI in 1974 at the household level and projecting backwards to 1969 using the 1969 level of AGI. Our results are robust to these choices. Additionally, our definition of income also includes capital gains. We are able to remove capital gains from our measure of income starting in 1994.

[12] To capitalize interest and dividend income into a measure of wealth we follow Smith, Zidar, and Zwick (2023).

[13] In particular, we are able to link individuals to their ASEC responses if they were included in the ASEC during the years 1973, 1979, 1981-1991, 1994, and 1996-2020.

To study income dynamics, we focus on a sample of individuals with a minimum degree of labor force attachment. To be included in our estimation sample, an individual must: (1) satisfy a minimum income requirement in at least 2 years, (2) satisfy the minimum income criterion in at least 50% of observations (inclusive) between the first and last year that they satisfy the minimum income criterion, and (3) be between the ages of 25 and 60. For conditions (1) and (2), we impose a minimum income criterion equal to $10,000 (in 2005 PCE dollars).[14] These sampling criteria result in a sample of 2.06 million individuals. When a household's income moves below our minimum cutoff, or is missing, we classify their income observation as missing and are able to retain them in the sample.[15]

Finally, we discuss how we remove the predictable component of household income, i.e., residualizing. We residualize income by removing age and year fixed effects as well as dummy variables for the number of adults in the household as in De Nardi et al. (2020).[16] Additionally, we exclude negative incomes from the residualization stage and treat those observations as part of the non-employed/non-filer category in the filter. Table 1 provides summary statistics for the households in our sample.

1.2 Motivating Facts: Rising Risk

To motivate our analysis, we present a set of simple data moments designed to proxy permanent and transitory income risk. These "simple" moments provide suggestive evidence that (1) permanent income risk has increased in the U.S. since the 1970s, (2) the variance of permanent income changes is U-shaped in prior income, and (3) permanent income risk has increased among high-income households.

We begin by summarizing changes in income volatility since the 1970s. In Figure 1, we plot the variance of (residual) log income changes over a 5-year horizon (black, solid line with circle markers) and 10-year horizon (red, dashed line with triangle markers). The figure shows that since 1969 there has been a steady increase in the variance of income changes at a 10-year horizon, while there have been increases and decreases in the variance of 5-year changes. As

[14] In results that are available upon request, we show that our results are robust to using alternative values of the minimum income cutoff. Part of the motivation for using a higher cutoff for 1040 income compared to W2 income (as in Braxton et al. (2025)) is that households do not have to file taxes if their income is below a given cutoff. In recent years these cutoffs have ranged from $12,950 for a single person under 65 to $25,900 for a married household filing jointly. See `https://www.irs.gov/newsroom/who-needs-to-file-a-tax-return` for additional details. *Link last accessed on May 5, 2024.*

[15] Note that a household's income can move below the minimum income cutoff due to spells of non-employment, choosing to not file their taxes if their income is below the cutoff, or if, due to large losses in business income, their AGI is negative.

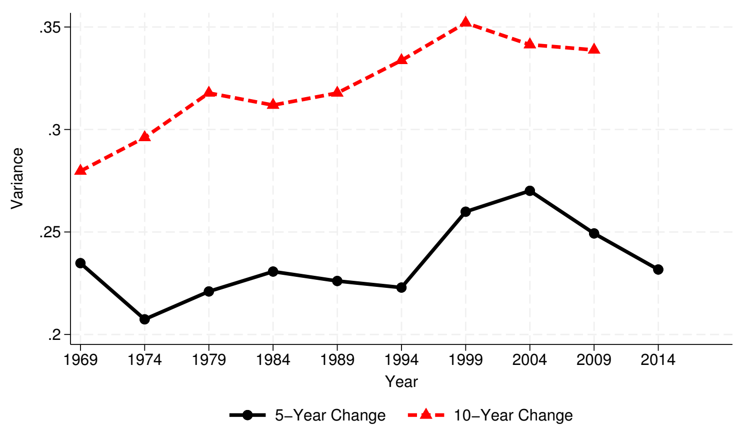
[16] We show in Appendix C.4.1 that we find similar results if we interact the number of adult fixed effects with time fixed effects.

Table 1: Summary Statistics

Variable	Mean
Real Income	$67,210
Age	41.1
Share Non-employed/Non-filing	6.1%
Share Male	50.1%
Number of adults in household	1.6
Observations	10,440,000
Individuals	2,060,000

Note: See Section 1.1 for sample selection criteria. Real income is measured in 2005 (PCE) dollars, and corresponds to adjusted gross income (AGI) less interest and dividend income. The variable "share non-employed/non-filing" is the share of individuals whose real income in a given year does not satisfy the minimum income criterion or is missing.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

Figure 1: Income Risk in the U.S. Since the 1970s



Note: Figure presents the variance of residual log income changes over a 5-year horizon (black, solid line with circle markers) and a 10-year horizon (red, dashed line with square markers).
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

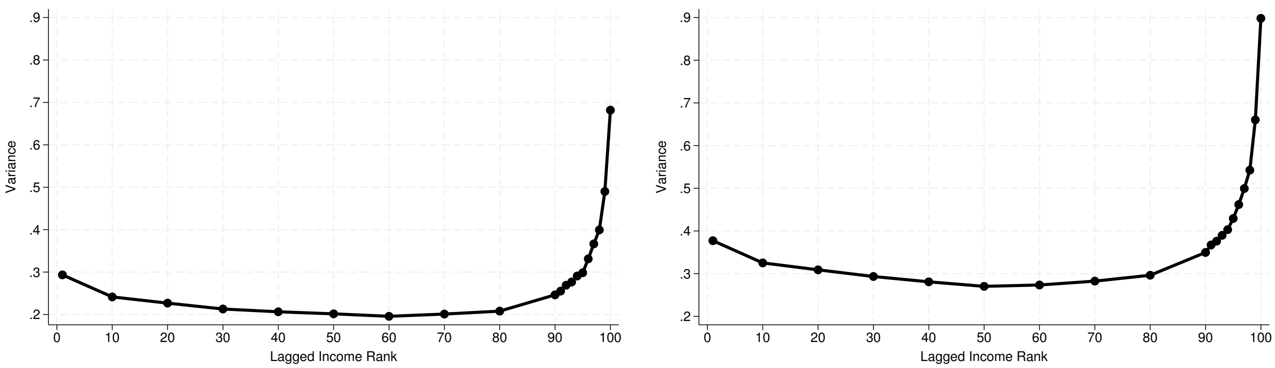
discussed in Braxton et al. (2025) and references therein, longer horizon changes in income risk are more reflective of permanent income risk as opposed to shorter horizon changes where transitory risk plays a larger role. Therefore, the steady increase in the variance of the 10-year income change likely reflects an increase in permanent income risk in the U.S. over this time period.

Second, we provide evidence that income risk is U-shaped in prior income. In Figure 2 we

Figure 2: Variance of Log Income Changes by Lagged Rank

(a) 5-Year Log Income Change

(b) 10-Year Log Income Change



Note: Figure presents the variance of residual log income changes over a 5-year horizon (Panel (a)) and a 10-year horizon (Panel (b)) as a function of lagged income rank.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

present the variance of 5-year income changes (Panel (a)) and 10-year income changes (Panel (b)) as a function of lagged income rank.[17] Both of these figures show that the variance of income changes decreases as a function of lagged income for low income households, then is relatively flat for much of the middle of the income distribution, before it increases substantially in the top of the income distribution.[18] This sharp increase in the variance of income changes in the far right tail, especially among 10-year earnings changes, provides our first piece of evidence that permanent income risk is convex.

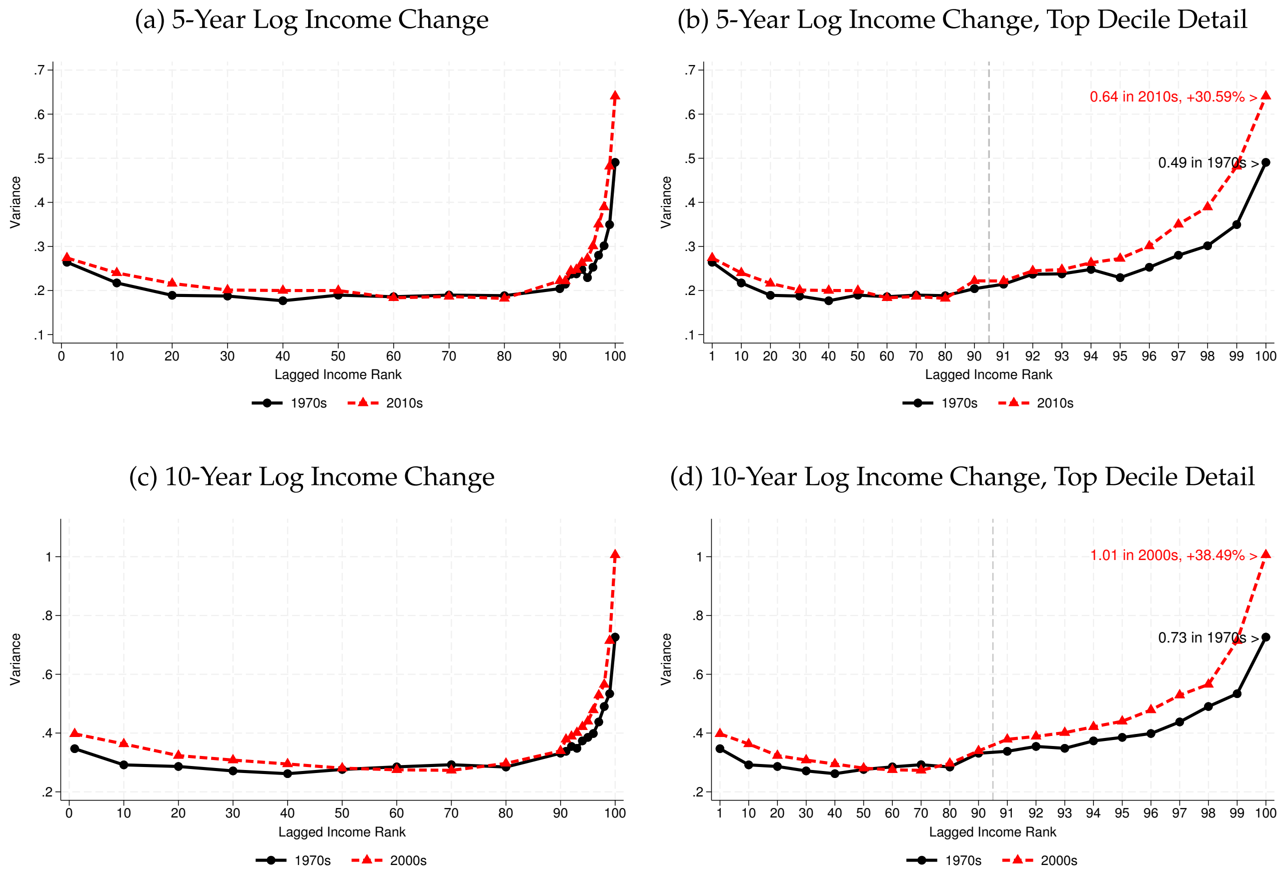
Lastly, we document how these measures of income risk have evolved over time across the income distribution. Panels (a) and (b) of Figure 3 plot the variance of residual log income changes over a 5-year horizon as a function of lagged income rank, comparing the 1970s to the 2010s. The changes are modest through most of the distribution, with the main increase occurring at the very top. At the 95th percentile, the variance rises by nearly 20%, and at the top percentile it rises by more than 30%.

Panels (c) and (d) show that this pattern is not limited to shorter-horizon income changes. Using 10-year income changes, and comparing the 1970s to the 2000s, we again find little change through much of the distribution but a sharp increase in dispersion at the top. At the top

[17] As we will discuss in greater detail in Section 2.1 we rank individuals using their lagged residual log income, and we rank individuals within year and age.

[18] Recent papers showing that the variance of income changes is U-shaped include Guvenen et al. (2014) and Guvenen et al. (2021). Relative to these papers we will decompose these income changes into their permanent and transitory components and examine time trends in the evolution of income risk across the distribution. Additionally, we use household level measures of income and incorporate business income into our estimates.

Figure 3: Variance of Log Income Changes by Lagged Rank and Decade



Note: The figure plots the variance of residual log income changes by lagged income rank. Black circles show the 1970s and red triangles show the later comparison decade. Panels (a) and (b) report 5-year income changes, comparing the 1970s to the 2010s; panels (c) and (d) report 10-year income changes, comparing the 1970s to the 2000s. The right panels re-plot the same estimates with additional visual space for the top decile, where ranks 91 through 100 are shown separately. The vertical dashed line marks the start of this top-decile region. Text annotations report the top-percentile variance in each decade and the percent change relative to the 1970s.
Source: 1973, 1979, 1981–1991, 1994, and 1996–2020 Current Population Survey Annual Social and Economic Supplement linked to 1040 records in 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, and 2019.

percentile, the 10-year variance rises from 0.73 in the 1970s to 1.01 in the 2000s, an increase of nearly 40%. Thus, the increase in income risk is concentrated among high-income households and is visible at both medium- and longer-run horizons.[19]

Figures 1, 2, and 3 provide suggestive evidence that income risk has increased and that the increase is concentrated among high-income households. Because these households hold a disproportionate share of wealth, changes in the risk they face may have important impli-

[19] We compare the 1970s to the 2000s for the 10-year horizon because our panel ends in 2019, preventing us from computing 10-year changes using the 2010s as the base decade.

cations for aggregate saving, the risk-free rate, and wealth concentration. The macro implications of these trends crucially depend on (1) the relative permanence of the income shocks, and (2) whether our econometric classification of shocks truly reflects risk (i.e., were the changes unanticipated). To address these two points, we next write down a tractable but rich permanent/transitory income process, and then we estimate it by filtering (e.g., Braxton et al. (2025)). This accomplishes two goals. First, it lets us distinguish the permanent and transitory components of rising income volatility. Second, our estimation procedure yields a panel of filtered income shocks for each individual at each point in time, which we use to validate that rich households do indeed behave as if our recovered income shocks are unanticipated.

2 Income Process and Estimation

We first describe the income process, which allows for shocks to permanent and transitory income to vary across the income distribution as well as over time. We then detail the way we estimate the process using the Kalman filter and an Expectations Maximization (EM) algorithm.

2.1 A Tractable Income Process with Flexible Dependence on Prior Income

We begin with a panel of income, $Y_{i,t}$, where $i \in \{1, \dots, N\}$ indexes households and $t \in \{1, \dots, T\}$ indexes years. For ease of presentation, when we exposit our income process, we think of each one-unit interval in t, i.e., from $t-1$ to t as representing five years.[20] Since we are interested in income risk, we residualize log income by removing the predictable component (e.g., age and time effects) of income.[21] We denote the resulting residual log income as $y_{i,t}$.

Following our earlier work (Braxton et al. (2025)), our income process explicitly includes years with zero (and negative) income as well as missing income observations, which can occur due to non-filing of taxes. Let $l_{i,t} = [l_{E,i,t} \; l_{N,i,t}]'$ denote a household's labor market status. Element $l_{E,i,t}$ equals one when household i is employed in year t and zero otherwise. Likewise, $l_{N,i,t}$ equals one when household i is non-employed/non-filing and zero otherwise. A household is employed when they earn more than our minimum income criterion $\bar{y}$ (i.e., $Y_{i,t} > \bar{y}$ where

[20] In Appendix B, we discuss how we translate an income process with a 1-year time step into a 5-year time step by exploiting the random walk nature of our income process, and provide evidence from the PSID that the frequency of observations does not materially impact the patterns we find for permanent income risk across the income distribution. We also group time dummies such that the 1970 time dummy corresponds to 1969, 1974 and 1979 (we group the initial 3 observations), the 1980 time dummy corresponds to 1984 and 1989, the 1990 time dummy corresponds to 1994 and 1999, and so on.

[21] We discuss how we remove the predictable components of income in Section 1.1.

$\bar{y} = \$10k$ as in Section 1) and classified as non-employed/non-filer otherwise.[22] We observe – and condition on – employment status $l_{i,t}$ when estimating the parameters of our income process. Under assumptions often satisfied by search models, the income process parameters can be estimated independently of the underlying process for $l_{i,t}$ (see Section 1 and Appendix A in Braxton et al. (2025) for a detailed discussion of this point). We then specify and parameterize the process for $l_{i,t}$ in Section 4, which will be governed by a separate set of parameters than those for the income process.[23]

The main innovation of this paper is to allow the shocks to permanent and transitory income to depend on where a household is in the income distribution as well as time. While our method is sufficiently tractable to characterize shocks by rich histories of prior income, our baseline approach makes income shocks a function of a household's lagged income rank, which we denote $r \in [0, 100]$. We determine a household's lagged income rank r by computing a household's percentile of lagged residual income (y_{-1}) within their age cohort a, and a given year t, i.e., $r = \text{Rank}(y_{-1}, t, a)$.[24]

For employed households, we model the process for observed income $y_{i,t}$ as the sum of permanent income $z_{i,t}$ and transitory income $\omega_{i,t}$. When a household is employed they draw their temporary income from a normal distribution with a variance $R(\cdot)$ that depends on their lagged income rank r, decade d as well as age a.[25] For households that are non-employed/non-filing, we set their residual log income to missing. We model income $y_{i,t}$ as evolving according

[22]As discussed in footnote 14, we show that our results are robust to using alternative values of the minimum income cutoff in results that are available upon request.

[23]We assume that labor market status $l_{i,t}$ is revealed before shocks to temporary and permanent income are revealed. We further assume that $l_{i,t} \perp z_i^{t-1} | (y_i^{t-1}, l_i^{t-1})$, which we refer to as augmented sequential exogeneity (ASQ) in Braxton et al. (2025). Conceptually, this assumption is that contemporary employment status is independent of lagged permanent income conditional on the history of income and employment status. We show in Braxton et al. (2025) that under ASQ the Kalman filter and smoother return the same paths of permanent income as under the assumption that employment status $(l_{i,t})$ is strictly exogenous. With the ASQ assumption, we also establish that the parameters for the employment process are separate from the parameters for the income process, and therefore can be estimated separately.

[24]For a household's first observation in the sample, we give them a lagged income rank of zero. For households with income below the minimum income cutoff, we use their value of residual log income from when they were last over the minimum income cutoff. Additionally, when a household is transitioning from being a non-employed/non-filer (N) to being employed (E), we give them a rank of zero in that period. In results that are available upon request, we show that our results are robust to the nature in which we classify lagged income ranks for new entrants and households exiting unemployment.

[25]As we discuss in more detail below, the assumption that shocks are normally distributed will buy us substantial tractability by allowing us to use an expectation maximization (EM) algorithm to estimate the parameters of our income process. However, despite the assumption of normally distributed shocks, our model still generates non-Gaussian features consistent with prior work (e.g., Guvenen et al. (2021) and references therein). Note that shocks are drawn from a normal distribution, conditional on their rank, age and decade. Thus, in the cross-section of households there is mixing of normal distributions, which generates non-Gaussian features. Additionally, since a household's future rank depends on the shocks they receive in the current period, households are mixing over normal distributions when they form expectations about their future income realizations.

to,

$$y_{i,t} = \begin{cases} z_{i,t} + \omega_{i,t}, & \omega_{i,t} \sim \mathcal{N}\big(0, R(r,d,a)\big) \quad \text{if } l_{E,i,t} = 1 \\ \cdot & \text{if } l_{E,i,t} = 0 \end{cases} \tag{1}$$

As in Blundell et al. (2008), we assume that permanent income $z_{i,t}$ evolves according to a random walk. We additionally assume that permanent income is subject to a drift $B_e(r,d,a)$ that depends on the household's employment status $e \in \{E, N\}$ as well as their lagged income rank r, decade d, and age a.[26] Additionally, permanent income is subject to shocks $\nu_{i,t}$, which are drawn from a normal distribution and depend on a household's employment status, lagged income rank, decade, and age. Given this formulation permanent income evolves according to,

$$z_{i,t} = \begin{cases} z_{i,t-1} + B_E(r,d,a) + \nu_{i,t}, & \nu_{i,t} \sim \mathcal{N}\big(0, Q_E(r,d,a)\big) \quad \text{if } l_{E,i,t} = 1 \\ z_{i,t-1} + B_N(r,d,a) + \nu_{i,t}, & \nu_{i,t} \sim \mathcal{N}\big(0, Q_N(r,d,a)\big) \quad \text{if } l_{E,i,t} = 0 \end{cases} \tag{2}$$

Households draw an initial value of permanent income, which we denote $z_{i,0}$. We assume that households draw this value of initial permanent income from a normal distribution with variance $Q_0(a,d)$, which varies by decade and age,

$$z_{i,0} \sim \mathcal{N}\big(0, Q_0(a,d)\big) \tag{3}$$

Equations (1)-(3) characterize our income process. Despite contemporaneous shocks being drawn from Gaussian distributions, this income process is actually a mixture model with tail risk (i.e., fatter tails than the standard normal distribution). Conditional on income in period $t-1$ (and other observables), households draw their income shocks in period t from a Gaussian distribution. However, income in future periods is a random variable, and it determines which Gaussian distribution the household draws shocks from. This forward looking randomness over which Gaussian distribution will be drawn introduces mixing and scope for tail risk. In addition to mixing, the employment process provides an additional source of non-Gaussian risk. Non-employment/non-filing generates large, discrete changes in permanent earnings.

Functional Forms. To facilitate estimation, we impose functional forms on the time, age, and rank dependence of parameters. In practice, we use B-splines to model the relationship between lagged income rank r and income shocks, allowing this relationship to vary by decade d. We denote these B-spline components with a superscript s. To account for changes in the age distribution of the U.S. population over time, we also allow the functions $Q(\cdot)$, $R(\cdot)$, and $B(\cdot)$

[26]Note the drift to permanent income can equivalently be thought of as the mean of the shock to permanent income.

to include a quadratic component in age, denoted by a superscript q. For example, we specify the variance of transitory income shocks as,

$$R(r,d,a) = \exp\left(\widehat{R}^s(r,d) + \widehat{R}^q(a)\right),$$

where $\widehat{R}^s(r,d)$ is the B-spline in rank interacted with decade dummies, and $\widehat{R}^q(a) = \lambda^q_{R,1}a + \lambda^q_{R,2}a^2$ is the quadratic in age.[27] Similarly, the variance, initial variance, and drift of permanent income are respectively given by,

$$Q_e(r,d,a) = \exp\left(\widehat{Q}^s_e(r,d) + \widehat{Q}^q_e(a)\right),\ Q_0(d,a) = \exp\left(\widehat{Q}_0(d) + \widehat{Q}^q_0(a,d)\right),\ B_e(r,d,a) = B^s_e(r,d) + B^q_e(a)$$

where $e \in \{E, N\}$ indexes employment status. We assume that $\widehat{Q}_0(d)$ captures decade-specific effects (i.e., decade fixed effects) and $\widehat{Q}^q_0(a,d)$ represents an age-dependent quadratic that is allowed to vary over time. Specifically, we estimate one set of quadratic parameters for the 1970s (including 1969), and a separate set for all subsequent decades.[28]

While richer income processes have been estimated in stationary (non-time dependent) environments (e.g. Arellano et al. (2017), De Nardi et al. (2020), and Guvenen et al. (2021)), our assumptions of linear additivity, conditional Gaussianity, and log-linear variances provide us with enough tractability to accomplish our goals of (1) allowing future income risk to depend on the path of prior income, (2) allowing past-income-dependence to evolve over time, and (3) being able to estimate the income process (and variants of the process with more flexible dependence on age, demographics, occupation etc.) on large administrative datasets. We next discuss how we tractably estimate the income process specified above.

2.2 Estimation

To estimate our income process, we adapt and apply the estimation routine from Braxton et al. (2025), which combines the Kalman filter with an Expectation Maximization (EM) algorithm. Below we discuss the role of each of these components of the estimation, and in Appendix A, we provide additional details about each step. We conclude this section by providing a brief "cookbook" on how to utilize the estimation procedure.

Kalman Filter. The first step of our estimation routine is to use the Kalman filter, which allows us to recover the path of permanent and transitory income for each household in our sample.

[27]Following Braxton et al. (2025), we model log variances to ensure that the estimated variances are positive.

[28]Allowing the age profile to shift between the initial and later periods is consistent with the approach in Braxton et al. (2025).

The Kalman filter naturally applies to our model, since it is in state space form (equation (1) is the observation equation and equation (2) is the state equation). However, when applying the Kalman filter algorithm, it is convenient to modify the state space representation to include lagged permanent income in equation (2) (see Appendix A.1). Moreover, the EM algorithm requires smoothed estimates of permanent income, which we recover by applying the Kalman smoother (see Appendix A.1).[29]

Expectation Maximization (EM) Algorithm. To run the Kalman filter and smoother, we need an estimate of the parameters of the income process. We obtain parameters of our income process via maximum likelihood estimation (MLE). While there are many different ways to maximize the likelihood (simple grid search, gradient descent, etc.), we adopt the approach of Dempster et al. (1977) and apply the Expectation Maximization (EM) algorithm. The benefit of utilizing an EM algorithm is that it yields closed-form updating formulas that resemble generalized least-squares (GLS) regressions, where the weights used in the regression adjust for filtering uncertainty. As we discuss in Appendix A.2, these closed-form expressions come from taking FOCs of the expected log-likelihood with respect to parameters. These closed-form expressions allow us to tractably update the parameters of our income process despite them being rich functions of observables.

Cookbook of Estimation Procedure. Finally, we conclude with a brief overview of our estimation routine. Our estimation routine proceeds as follows:

i. Guess an initial set of parameters for the income process, denoted θ_0.

ii. Using the current estimate of parameters θ_0, run the Kalman filter and smoother.

iii. Using the estimates from the Kalman filter and smoother steps, update the parameters using the GLS style formulas from the EM algorithm. Denote the updated parameters as θ_1.

iv. Repeat steps (ii.)-(iii.) until the parameters have converged.

In Appendix A.3, we use a series of Monte Carlo exercises to show that: (1) our income process is identified, and (2) our method can accurately recover the parameters of the income

[29] Additionally, when the estimates of the state vector are of interest, as they are in our application, Hamilton (1994) comments that we can improve the inference about the historical values of the state vector in the middle of the sample by using the Kalman smoother.

process as well as the household level estimates of permanent income. We also show in Appendix A.3 that an estimation approach in the GMM tradition is not able to accurately recover the parameters of an income process where the parameters depend upon lagged income ranks.

Next, we apply our income process to the tax panel and analyze the results.

3 Estimation Results

After estimating our income process on the tax panel, we find that permanent income risk has increased, especially among high-income households. We then validate that high-income households do in fact face income risk by showing that large declines in permanent income are associated with various indicators for economic hardship (e.g., early 401K withdrawals, moving to lower income neighborhoods, etc.). Finally, we examine how saving responds to changes in income risk and find that in response to increases in permanent income risk, households save more, especially high-income and younger households.

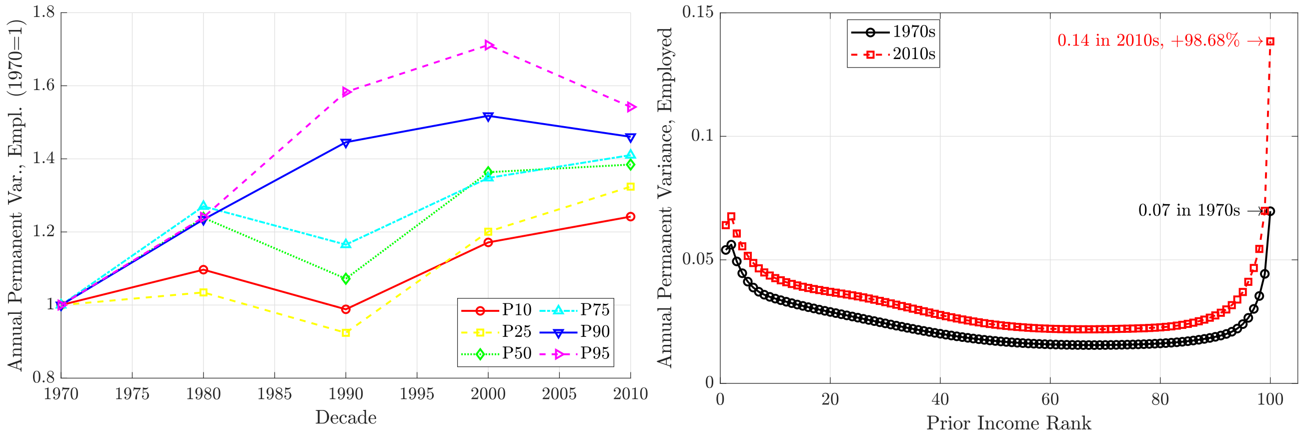
3.1 Permanent and Transitory Risk Across Time and Income

We start by showing the evolution of permanent income risk among the employed since the 1970s for selected percentiles of the (lagged) income distribution in panel (a) of Figure 4. The pink, dashed line with triangle markers, shows the evolution of permanent income risk for households at the 95th percentile of the lagged income distribution. The figure shows that since the 1970s, permanent income risk for these households steadily increases between the 1970s and the 2000s. Over this time period, the variance of shocks to permanent income increased by over 70% for these households before declining in the 2010s. Overall these high-income households have seen their permanent income risk increase by approximately 55% since the 1970s. The blue solid line with triangle markers shows the evolution of permanent income risk among households at the 90th percentile of the income distribution and shows that these households have faced a similar pattern of rising income risk between the 1970s and the 2010s. For these households, income risk has increased by over 45% since the 1970s.

The red and yellow lines in Panel (a) of Figure 4 present the evolution of permanent income risk among lower income households, corresponding to the 10th and 25th percentiles, respectively. Lower income households have experienced a different evolution of permanent income risk relative to high-income households. Permanent income risk was effectively unchanged for these households between the 1970s and 1990s, before increasing between the 1990s and 2010s. Despite the increases over the past 20 years, the increases in permanent income risk have been

Figure 4: Permanent Income Risk Among Employed: Over Time and By Lagged Income

(a) Time Series of Selected Percentiles (b) Distribution of Shocks, 1970s & 2010s



Note: Figure presents the results of estimating the income process in Section 2.1. Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income rank for the 1970s (black, solid line with circle markers) and the 2010s (red, dashed line, with square markers). Note in panel (b) we present an annualized variance.

Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

more muted for these lower income households, increasing by between 20% and 30% since the 1970s.

While the results presented in Panel (a) of Figure 4 show the evolution of permanent income risk for each decade by selected percentile, in Panel (b) of Figure 4 we show the full profile of shocks to permanent income by lagged income rank for the 1970s (black, solid line with circle markers) and 2010s (red, dashed line with square markers).[30] The figure shows that permanent income risk is U-shaped across the income distribution. Permanent income risk decreases from the bottom of the lagged income distribution until approximately the 75th percentile of the income distribution, at which point permanent income risk starts to increase again. We find that the increases in permanent income risk as a function of lagged rank are especially steep as we move towards the very top of the income distribution. We refer to this phenomenon as *convex permanent income risk* and in Section 4.3 examine its quantitative implications.

[30] In panel (b), we present an annualized estimate of the variance of shocks to permanent income among the employed. We annualize our estimates by dividing by 5. Additionally, our estimation routine produces an estimate of the mean shock to permanent income among the employed by lagged income rank for each decade. We present these estimates in Appendix C.1. These estimates reveal substantial mean reversion in permanent income. Additionally, we find that in the 2010s the mean shock to permanent income has increased for the rich relative to the 1970s.

Comparing the 1970s to the 2010s, we find that there has been an increase in permanent income risk across the entire income distribution (as shown in Panel (a)); however, the increase is especially large towards the top of the income distribution. Averaging over the households in the top 5% of the income distribution, we find that the variance of shocks to permanent income has increased by nearly 70%. If we look at the very top of the income distribution, we find that permanent income risk has effectively doubled. Thus, high earners have seen a substantial acceleration of permanent income risk over the past 50 years.

We next examine the evolution of transitory income risk over time and across the income distribution. Panel (a) of Figure 5 presents the variance of shocks to transitory income (i.e., transitory income risk) as a function of lagged income rank for the 1970s (black, solid line with circle markers) and 2010s (red, dashed line with triangle markers). The figure shows that transitory income risk is effectively flat for the bottom 80 percent of the income distribution and then starts to increase as we move out into the right tail of the income distribution. Comparing the 1970s and 2010s, we find that the level of transitory income risk is effectively unchanged for the bottom 95% of the income distribution. However, for households in the top 5% of the income distribution, transitory income risk is higher in the 2010s relative to the 1970s. In particular, for households at the very top of the income distribution the variance of shocks to transitory income has increased by over 60% since the 1970s. Combining these results with those presented in Figure 4, we find that high-income households are exposed to the largest amount of permanent and transitory income risk while employed and that this risk has been increasing since the 1970s.

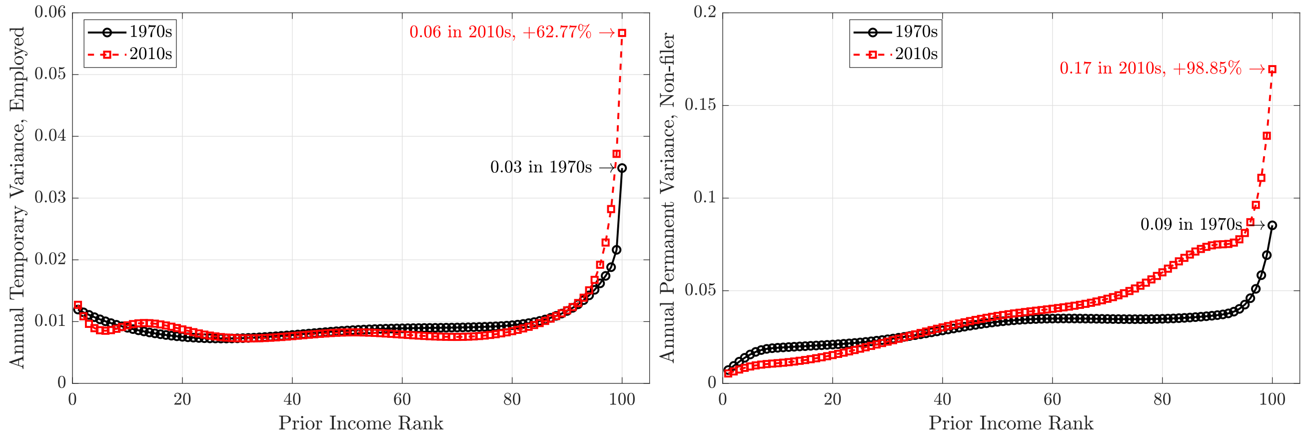
A feature of our income process and estimation routine is that it allows us to estimate the risk that households face during periods of non-employment or when they are not filing their taxes. In Panel (b) of Figure 5, we present the variance of shocks to permanent income during periods of non-employment/non-filing for the 1970s and 2010s.[31] The figure shows that the variance of shocks to permanent income during periods of non-employment is increasing in lagged income rank (from when a household was last employed). Comparing the 1970s to the 2010s, we find that the variance of shocks to permanent income has increased during periods of non-employment and non-filing for households above the 60th percentile of the income distribution. As we move out into the right tail of the income distribution, we find larger increases in permanent income risk over time, and at the very top of the distribution find that it has nearly doubled since the 1970s.

In summary, high-income households face the highest risk to permanent income both while

[31] In Appendix C.1, we present the mean of shocks to permanent income in periods of non-employment/non-filing as a function of lagged income rank and over time. We find that the decline in permanent income from periods of non-employment/non-filing is larger for high-income households than for lower income households.

Figure 5: Transitory Risk and Permanent Risk Among Non-Employed/Non-Filers

(a) Distribution of Transitory Risk, Employed (b) Distribution of Permanent Risk, Non-Employed



Note: Figure presents the results of estimating the income process in Section 2.1. Panel (a) plots the full profile of shocks to transitory income among the employed as a function of lagged income rank for the 1970s and 2010s. Panel (b) plots the full profile of shocks to permanent income among the non-employed/non-filing as a function of lagged income rank for the 1970s and the 2010s. In both figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

employed and non-employed/non-filing as well as the highest transitory income risk.[32] We additionally find that these measures of income risk have increased over time for high-income households. We next discuss a series of additional results about the evolution of income risk over time and across the income distribution.

Risk Among Self-Employed. The results presented thus far have pooled together all individuals and examined the evolution of income risk across the income distribution and over time. Next, we separately analyze the evolution of income risk for individuals who we designate as "self-employed" versus individuals who we designate as "non self-employed." To do so, we leverage our ability to link the sample of 1040 tax returns to the CPS-ASEC, which asks respondents about the *class of worker* they were in the prior year, i.e., were they self-employed, working for wage and salary, etc. This measure of self-employment includes both incorporated and unincorporated business owners, which is a unique benefit of our CPS-tax linkage.[33] Based on the responses to this question, we split our sample into the self-employed and the non

[32]Finally, our income process also allows the variance of the initial draw of permanent income to vary by decade. We show in Appendix C.1 that the variance of the initial draw of permanent income has been steadily increasing since the 1970s.

[33]See Bowler (2006) for detailed discussion of who is classified as self-employed in the CPS.

self-employed and estimate our income process separately for each group.[34]

Figure 6 presents the profiles of permanent income risk for the self-employed (Panel (a)) and non self-employed (Panel (b)) from estimating our income process separately by self-employment status.[35] These figures highlight several points about the differences in risk faced by the self-employed compared to the non-self employed and how the risk in each of these groups has evolved over time. First, comparing the profiles of risk for the self-employed to the non self-employed, we observe that self-employed individuals face higher *levels* of permanent income risk at almost every point in the income distribution in both the 1970s and the 2010s. Second, while we find that permanent income risk has increased across the income distribution for both the self-employed and non-self employed, the increase at the top of the income distribution for the self-employed is especially large. On average, for self-employed individuals in the top 5% of the income distribution permanent income risk has increased by over 130% and at the very top of the income distribution permanent income risk has increased by over 175%. While the high-income non self-employed have also seen substantial increases in permanent income risk, the magnitude of the increase for these households is smaller.

Robustness of Income Risk Patterns We conclude this subsection by summarizing a series of robustness results.

Alternative income definitions. In Appendix C.2, we show that our results are robust to a series of alternative definitions of income. We show that our results are robust to using adjusted gross income (AGI) (Appendix C.2.1), wage and salary income (WSI) (Appendix C.2.2), as well as removing capital gains from our baseline measure of income (Appendix C.2.3).

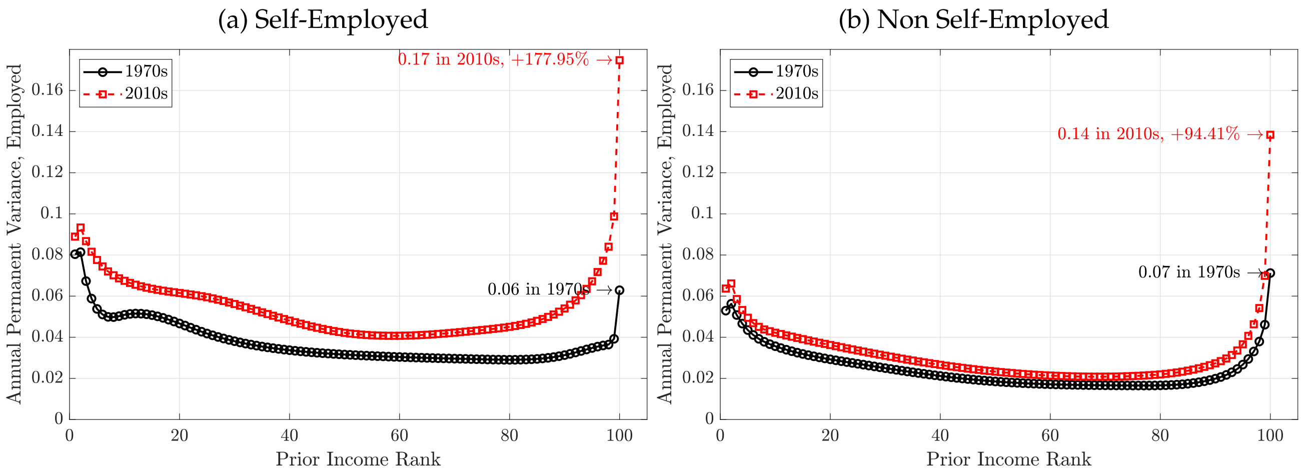
Alternative sampling. We show in Appendix C.3, that our results are robust to using a 2% random sample of all 1040s.

Demographic composition. In Appendix C.4.1, we show that our results are robust to interacting the fixed effects for year and number of adults in the household as part of our residualization process, which we interpret as evidence that our results are not driven by changes in labor force composition over time. In Appendix C.4.2, we obtain similar results when ranking individuals within their 2-digit occupation, indicating that our findings are not driven by shifts in the occupational distribution over time. Finally, in Appendix C.4.3, we estimate a version of

[34] In estimating the income process separately for each group, we also residualize earnings within each group. We rank individuals within the full sample, so that a given rank r corresponds to the same average income level for both the self-employed and the non-self-employed. Finally, our definition of self-employment combines both incorporated and unincorporated self-employed individuals; our results are robust to restricting the sample to the incorporated self-employed.

[35] In Appendix C.1.1, we present the profiles of transitory income risk and permanent income among the non-employed risk for the self-employed and non-self-employed. We find relatively minor differences in the self-employed and non self-employed along these dimensions of income risk.

Figure 6: Permanent Income Risk Among Employed by Self-Employment Status



Note: Figure presents the results of estimating the income process in Section 2.1 where the parameters are allowed to differ by self-employment status as reported in the ASEC. Panel (a) plots the full profile of shocks to permanent income among the self-employed as a function of lagged income rank for the 1970s and the 2010s. Panel (b) plots the full profile of shocks to permanent income among the non self-employed as a function of lagged income rank for the 1970s and the 2010s. In both figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

our income process where the profile of shocks across the income distribution and over time differs by whether or not an individual is above/below age 40. We find that permanent income risk has increased among both younger and older high-income households.

3.2 Do High-Income Households Really Face Income Risk?

In Section 3.1, we argued that high-income households are exposed to large and rising permanent income risk. One concern with this interpretation is that the income changes among these high-income households, which underlie our estimates, may not reflect risk. In this section, we examine how observable indicators of financial distress align with large declines in permanent income, and how these relationships evolve across the income distribution.

Let $Y_{i,t}$ be an indicator variable that is informative about an individual undergoing financial distress (e.g., an early 401(k) withdrawal, moving to a lower income ZIP code, etc.). Let $D^P_{i,t}$ indicate whether individual i experienced a 1 standard deviation (or larger) decline in permanent income from $t-5$ to t.[36] Finally, let $X_{i,t}$ be a vector of controls that includes fixed effects

[36]Let $z_{i,t}$ denote our estimate of permanent income for individual i in period t from the Kalman step of our estimation routine. Define $\Delta z_{i,t} = z_{i,t} - z_{i,t-5}$ as the five-year change in permanent income between periods $t-5$

for lagged income rank, year, age, ventiles of transitory shocks, and the number of adults in the household. The specification we estimate is,

$$Y_{i,t} = \alpha + \beta D^P_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t} \tag{4}$$

The coefficient of interest is β, which summarizes the impact of a 1-SD decline in permanent income on the outcome variable. We additionally estimate equation (4) across the income distribution to examine how households in different positions of the income distribution respond to income shocks.

Early 401(k) Withdrawals. Our first validation exercise examines the link between large permanent income declines and early 401(k) withdrawals. Using tax form 1099-R, we observe when an individual makes a 401(k) withdrawal as well as the size of the withdrawal. To highlight the response to risk, we focus on "early withdrawals," which we define to be withdrawals that occur before age 55. To line up with the five-year timing of our income data from the 1040s, we analyze withdrawals of at least $1,000 in any year between $t-4$ and t. Further, we require that an individual made at least $4,000 worth of contributions into their 401(k) plan between the years $t-8$ and $t-5$.[37] This final condition is to ensure that we are considering individuals who have a 401(k) plan with contributions that can be withdrawn.[38]

Panel (a) of Figure 7 presents the results of estimating equation (4) where the outcome variable of interest is having an early 401(k) withdrawal. The blue bar reports the regression coefficient for a 1-SD decline in permanent income among our full sample of households. The coefficient indicates that in response to a 1-SD decline in permanent income, the likelihood that a household has an early 401(k) withdrawal increases by approximately 6.5 percentage points.[39] In our sample, approximately 31.5% of households will make an early 401(k) withdrawal over a 5-year period. Thus, a large decline in permanent income increases the likelihood of an early withdrawal by roughly 20% relative to the sample average, consistent with our estimates capturing meaningful income risk.

We next examine how early withdrawals vary over the income distribution by estimating

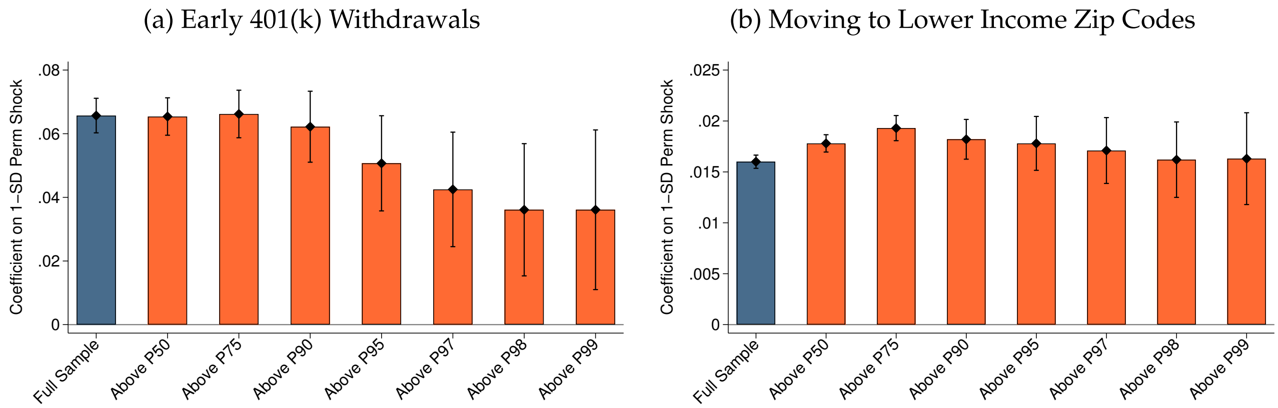
and t. Let $\sigma_{r,t}$ denote the standard deviation of shocks to permanent income for individuals with lagged income rank r in period t. We define the indicator $D^P_{i,t}$ to equal one if $\Delta z_{i,t} < -\sigma_{r,t}$ for an individual with lagged rank r, and zero otherwise.

[37]We utilize Box 12 on an individual's W-2 to measure the amount of 401K contributions that an individual makes in a given year.

[38]These conditions for considering early 401K withdrawals mirror those considered in Choukhmane et al. (2024), but adapted to the 5-year reporting of income in our data.

[39]For households that make an early 401(k) withdrawal, the average size of the withdrawal is approximately $32k.

Figure 7: Response to a 1-SD Decline in Permanent Income



Note: Figure presents the results of estimating equation (4) where the outcome variable of interest is: (1) having an early 401(k) withdrawal (Panel (a)), and (2) moving to a lower income ZIP code (Panel (b)). The bars correspond to the coefficient for the impact of having a 1-SD decline in permanent income. The black bars correspond to a 95% confidence interval using robust standard errors.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

equation (4) separately for households above a given lagged earnings centile. The orange bars in Figure 7 show that even among individuals in the top 5% of the income distribution, a 1-SD shock to permanent income increases their likelihood of an early 401(k) withdrawal by over 5 percentage points. Even at the very top of the income distribution, a 1-SD decline in permanent income still increases the likelihood of having an early 401(k) withdrawal by over 3.5 percentage points, indicating that these responses remain economically meaningful even among the highest-income households.[40]

Moving to Lower Income ZIP Codes. Our second validation exercise examines an alternative adjustment margin through which households respond to large income declines: moving to a lower income neighborhood. For all individuals in our sample, we observe a panel of residential ZIP codes as part of their 1040 tax form. Using a 5% random sample of 1040s, we measure the annual median adjusted gross income (AGI) of each ZIP code in our panel. We then define a move to a lower income neighborhood whenever an individual changes ZIP codes from $t-5$ to t and the median income at the destination ZIP code is at least 30% lower.[41]

[40] Among households in the top 5% of the income distribution, 27.2% make an early 401(k) withdrawal over a five-year period, compared to 26.8% among those in the top 1%. Conditional on making a withdrawal, the average amounts are approximately $46,000 and $49,000, respectively.

[41] In results that are available upon request, our results are robust to using mean income within a ZIP code as well as alternative cutoffs for cross-ZIP income changes.

Panel (b) of Figure 7 presents the results of estimating equation (4) where the outcome of interest is moving to a lower income ZIP code. The blue bar shows the impact of having a 1-SD decline in permanent income on the likelihood of such a move in our full sample of households. The coefficient indicates that these large declines in permanent income are associated with an increase in the likelihood of moving to a lower income ZIP code by approximately 1.6 percentage points. This increase is economically meaningful relative to a sample average of 5.9% over a five-year period.

As above, we next examine how this relationship varies across the income distribution by estimating equation (4) separately for households above a given lagged earnings centile. The orange bars in Figure 7 show that the effect of large declines in permanent income on the likelihood of moving to a lower income ZIP code is quite stable across the income distribution. Even at the very top of the income distribution, a 1-SD decline in permanent income increases the likelihood of moving to a lower income ZIP code by approximately 1.6 percentage points, indicating that these responses remain economically meaningful even among the highest-income households.[42]

Taking Stock. In this section, we've shown that in response to a large decline in permanent income, households respond by making early 401(k) withdrawals and moving to lower income neighborhoods. These results show that our econometric classification of shocks aligns with observable measures of financial hardship, even among the top 1% of the income distribution. These results suggest that high-income households do in fact face income risk. While these results examine how households respond to realized shocks, we next examine how changes in risk (i.e., changes to the variance of shocks) affect savings behavior.

3.3 Does Greater Income Risk Impact Savings?

A central prediction of quantitative models with incomplete markets (e.g., Bewley, Huggett, and Aiyagari) is that households facing greater income risk accumulate more assets in order to self-insure against adverse shocks. In this section, we empirically examine the relationship between income risk and savings by exploiting variation in permanent and transitory income risk across occupations and over time, while holding constant households' income and other observable characteristics.[43] We then use the estimated savings response to income risk to discipline the quantitative model introduced in Section 4.

[42]Among households in the top 1% of the income distribution, 7.9% move to a lower income ZIP code over a five-year period.

[43]This approach follows a long tradition in the precautionary savings literature that exploits occupation-level variation in income risk to study savings behavior (e.g., Carroll and Samwick (1997), Boar (2021)).

For this analysis we measure income risk by occupation and over time. Specifically, we separately estimate permanent and transitory income risk over time for each of the 334 time-consistent occupation codes developed by Autor and Dorn (2013).[44] Individuals are assigned to an occupation based on their first reported occupation in the ASEC. We summarize income risk using occupation level measures of permanent and transitory income variability. Let $Q_{o,E,t}$ denote the variance of permanent income shocks for employed individuals in occupation o at time t, and let $R_{o,t}$ denote the corresponding variance of transitory income shocks.[45]

To examine how income risk affects savings behavior, we use capitalized measures of wealth and estimate how changes in wealth respond to variation in occupation level income risk. We build asset positions by capitalizing interest and dividend income from tax returns, following Smith et al. (2023). This procedure yields estimates of wealth held in savings accounts, stocks and bonds for every household between 1974-2014.[46] Let $b_{i,t}$ denote the estimated asset levels, where i indexes households and t indexes time. Define $\Delta_h b_{i,t} = (b_{i,t+h} - b_{i,t})/Y_{i,t}$ as the change in wealth relative to income for individual i between periods t and $t+h$.[47] Let $X_{i,t}$ denote a vector of controls, which includes the mean permanent shock (for each employment status and occupation o in year t), as well as fixed effects for lagged income rank, centiles of lagged wealth by year, age, number of adults in the household and 2-digit occupation. We estimate specifications of the form:

$$\Delta_h b_{i,t} = \alpha + \beta_{Q_E} Q_{o,E,t} + \beta_{Q_N} Q_{o,N,t} + \beta_R R_{o,t} + \Gamma X_{i,t} + \epsilon_{i,t}. \tag{5}$$

Equation (5) relates changes in household wealth to variation in occupation-level income risk, while flexibly controlling for income, wealth, and demographic characteristics. The coefficients of interest in equation (5) are β_j for $j \in \{Q_E, Q_N, R\}$, which capture how differences in income risk across occupations translate into differences in savings behavior, holding constant income rank. To isolate the effect of risk from changes in expected income, we include controls for the mean occupation-level permanent income shock. We also condition on lagged income rank, which limits comparisons to households with similar income levels, and we include fixed

[44] Additionally, in this estimation, we allow both the mean and variance of income shocks to vary with age within each occupation (via an age quadratic), and we residualize income separately by occupation. We do not condition on income rank, as many occupations do not span the full income distribution.

[45] We additionally define $Q_{o,N,t}$ as the permanent income risk for non-employed or non-filing individuals in occupation o at time t. We also construct occupation-level measures of mean permanent income shocks, denoted $B_{o,E,t}$ and $B_{o,N,t}$, which we include as controls to separate changes in risk from changes in mean income.

[46] See Appendix D for details. We thank Eric Zwick for sharing data on dividend capitalization factors. Our 1040 sample does not include dividend income in the year 1969. Additionally, the capitalization index for dividends, which we obtain from Smith et al. (2023), ends in the year 2016.

[47] We restrict the sample to individuals with income exceeding \$1,000 (in 2005 PCE dollars).

Table 2: Income Risk and Changes in Savings Behavior

Dependent variable: 5-year change in wealth to income	(1)	(2)	(3)	(4)
Q_E	0.471***			0.468***
	(0.0951)			(0.0961)
Q_N		0.00319		0.00287
		(0.00228)		(0.00181)
R			0.194***	0.189***
			(0.0598)	(0.0592)
Controls	Y	Y	Y	Y
Lagged Wealth X Year FE	Y	Y	Y	Y
Lagged Income Rank FE	Y	Y	Y	Y
2-Digit Occ. FE	Y	Y	Y	Y
R-squared	0.048	0.048	0.048	0.048
No. Obs.	4,651,000	4,651,000	4,651,000	4,651,000

*Note: Table presents the results of estimating equation (5), where the dependent variable is the 5-year change in wealth to income. We measure wealth using the capitalization method of Smith et al. (2023) on interest and dividend income. Income risk is measured at the occupation level as described in Section 3.3. Controls include the mean shock to permanent income during periods of employment as well as non-employment non-filing in an occupation and year as well as fixed effects for age and the number of adults in the household. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level, where occupations are classified using Autor and Dorn (2013) occupation codes. *** p<0.01, ** p<0.05, * p<0.1*
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

effects for 2-digit occupations to ensure that identification comes from variation in income risk within broadly similar types of work.

Table 2 presents the results of estimating equation (5), where we measure the change in wealth to income over a 5-year horizon.[48] For ease of exposition, we introduce the measures of income risk sequentially. In column (1) of Table 2, we show how changes in wealth to income respond to variation in occupation level permanent income risk. The positive and statistically significant coefficient on permanent income risk (Q_E) indicates that within a given income rank, individuals who are in occupations that face greater permanent income risk have a larger change in wealth to income. In particular, in response to a 0.1 increase in permanent income variance, wealth increases, on average, by 4.7% of prior income, ceteris paribus. Thus, in response to greater permanent income risk, households respond by saving more.

[48] In results that are available upon request, we find that our results are robust to using a 10-year horizon to measure changes in wealth to income.

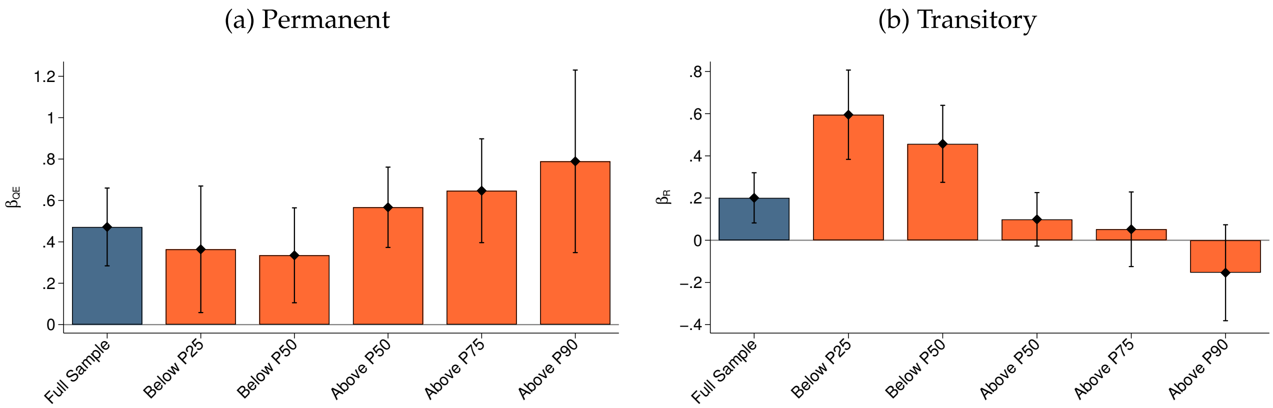
We next examine the response to other measures of income risk. In column (2) of Table 2, we examine how permanent income risk when non-employed/non-filing impacts savings behavior. The coefficient on permanent income risk when non-employed/non-filing (Q_N) indicates that greater exposure to permanent risk while non-employed/non-filing *does not* impact changes in wealth to income in an economically or statistically significant manner. In column (3) of Table 2, we examine how transitory income risk impacts savings. The positive and statistically significant coefficient on transitory income (R) indicates that in response to greater transitory income risk households respond by increasing their wealth to income. In response to a 0.1 increase in an occupation's transitory income variance, individuals respond by increasing their wealth by 1.94% of prior income, ceteris paribus.

Finally, Column (4) considers our measures of income risk jointly and controls for the mean of shocks to permanent income. The coefficient estimates in column (4) show that we obtain very similar estimates when using all three measures of risk jointly and when controlling for the mean shocks to permanent income. We continue to find that greater exposure to permanent and transitory income risk is associated with increases in savings. We next examine the heterogeneity in the response of savings to permanent and transitory income risk.

Heterogeneity. We examine the heterogeneity in how savings responds to income shocks by estimating equation (5) for different sub-samples of our population. We focus on the response to permanent and transitory income risk as those were the parameters that we found impacted savings above, and consider these measures of risk sequentially. In Figure 8, we examine how savings responds to permanent (panel (a)) and transitory (panel (b)) income risk for different regions of the income distribution. The navy bar in panel (a) of Figure 8 presents our baseline estimate of how individuals respond to permanent income risk. The orange bars then presents the response of savings for different regions of the income distribution. Clearly, the response to permanent income risk is increasing across the income distribution. In particular, for individuals below the median, in response to a 0.1 increase in permanent income variance, wealth increases by 3.4% of prior income. For individuals, above the median they increase their wealth by 5.7% of prior income. Thus, we find that higher income households increase their savings more in response to increasing permanent income risk compared to lower income households.

In panel (b) of Figure 8, we show that the response of savings to transitory income risk is decreasing across the income distribution. For individuals below the median, wealth increases by 4.6% of prior income in response to a 0.1 increase in transitory variance. Conversely, for individuals above the median, wealth to income increases by less than 1% in response to a 0.1 increase in transitory income variance, and this increase is not statistically different from zero

Figure 8: Income Risk and Changes in Savings Behavior by Prior Income Rank



Note: Figure presents the results of estimating equation (5) in the full sample (navy bar) as well as across the income distribution (orange bars). Panel (a) presents the response of wealth to income to permanent income risk, while panel (b) presents the response of wealth to income to transitory risk. The bars represent the coefficient estimates and the whiskers represent a 95% confidence interval. To compute the 95% confidence interval, we cluster the standard errors by occupation where occupations are measured using the classification from Autor and Dorn (2013).

Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

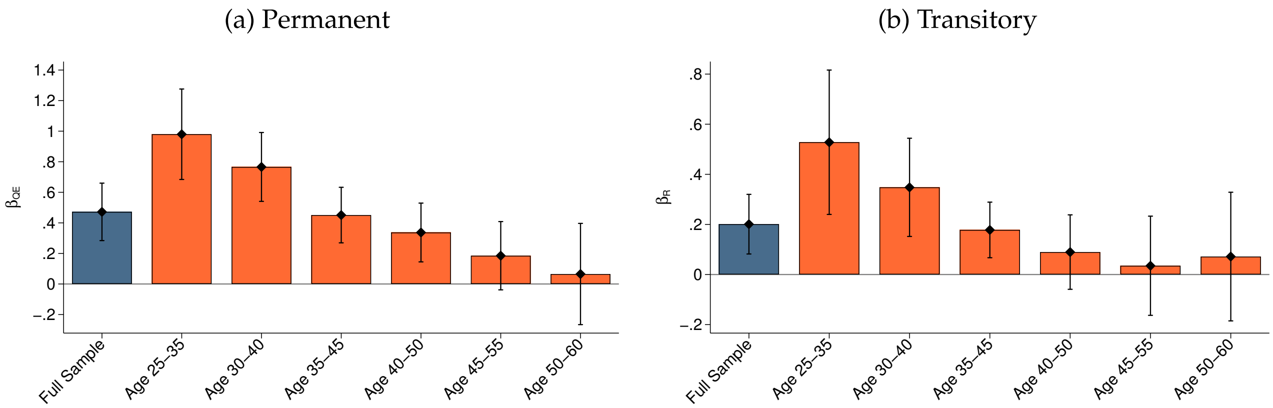
(t-stat = 1.53).

We next examine the response of savings to income risk for individuals of different ages. In panel (a) of Figure 9, we show that the response of savings to permanent income risk is decreasing in the age of an individual. For individuals between the ages of 25 and 34, in response to a 0.1 increase in permanent income variance, wealth increases by 9.8% of prior income. Conversely, for individuals between the ages of 50 and 60, the response is not statistically different from zero. Similarly, panel (b) shows that the response of savings to transitory income risk is decreasing in age. For individuals between the ages of 25 and 34, in response to a 0.1 increase in transitory variance, wealth increases by 5.3% of prior income, while for individuals between the ages of 50 and 60 there is effectively no change in wealth.[49]

In this section, we've shown that savings increases in response to permanent and transitory income risk. The response to permanent risk is driven by high-income and younger individuals, while the response to transitory income risk comes from lower income and younger individuals. We will use these estimates to validate our quantitative model in Section 4.

[49]The larger savings response of young households aligns with the "buffer stock" theory of savings (e.g., Carroll (1997) and Gourinchas and Parker (2002).)

Figure 9: Income Risk and Changes in Savings Behavior by Age



Note: Figure presents the results of estimating equation (5) for workers of different ages. Panel (a) present the response of wealth to income to permanent income risk, while panel (b) presents the response of wealth to income to transitory risk. The bars represent the coefficient estimates and the whiskers represent a 95% confidence interval. To compute the 95% confidence interval, we cluster the standard errors by occupation where occupations are measured using the classification from Autor and Dorn (2013).
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

Taking Stock. In this section, we've shown that permanent and transitory income risk has increased for top-earners in the U.S. since the 1970s. We've additionally shown that in response to increasing permanent income risk, individuals respond by increasing their savings, especially among high earners and younger individuals. In the next section, we introduce a life-cycle Bewley-Huggett-Aiyagari model with our income process. We then use the empirical estimates from this section to discipline the quantitative model. Using the quantitative model, how then examine how both convex and rising income risk affect savings at the top, wealth inequality, and interest rates.

4 Model

To examine how income risk at the top shapes savings behavior and interest rates, we integrate our income process into a finite lifecycle Bewley-Huggett-Aiyagari model. There is a unit measure of overlapping generations of households, where a household's age is denoted by $t \in \{1, \dots, T\}$. Households work for the first T_W periods of life and then retire for the final T_R periods, so that $T = T_W + T_R$. In our baseline calibration, one model period corresponds to five years, households work from ages 25 to 60, and then retire from ages 65 to 95.

Households save $(b > 0)$ and borrow $(b < 0)$ at interest rate r_f using a risk-free asset

$b \in [\underline{B}, \infty]$, subject to the natural borrowing limit $\underline{B} \leq 0$. Their asset choices maximize the present value of their flow utility over consumption $u(c)$, discounted at rate β. In the terminal period of life, households have warm-glow bequest motives, $\phi(b)$. Household preferences are thus given by,

$$\mathbb{E}\Big[\sum_{t=1}^{T} \beta^{t-1} u(c_t) + \beta^T \phi(b_{T+1})\Big].$$

During working life, households face risky streams of permanent ($z \in \mathbb{R}$) and transitory income ($\omega \in \mathbb{R}$). The magnitude of income risk depends on their age t, employment/filing status $e \in \{E, N\}$ (where E denotes employed, and N denotes non-employed/non-filer), and their age-dependent rank in the income distribution $r \in \{0, 1, \ldots, 100\}$ (where $r = Rank_t(z, \omega, e)$). The transition rate across employment/non-filer status is given by $p_t(e'|z, \omega, r, e)$. Lastly, we assume households have a deterministic lifecycle profile of income ($\kappa_t \in \mathbb{R}$), and we model taxes following Heathcote et al. (2017).

We summarize pre-tax labor income during working life using the function $w_t(z, \omega, e)$,

$$w_t(z, \omega, e) = \begin{cases} \exp(\kappa_t + z + \omega) & \text{if } e = E \\ \gamma \exp(\kappa_t) & \text{if } e = N. \end{cases}$$

After-tax income $\widetilde{w}_t(z, \omega, e)$ is governed by progressivity parameter α and location parameter λ,

$$\widetilde{w}_t(z, \omega, e) = \lambda w_t(z, \omega, e)^{1-\alpha}.$$

In retirement, households no longer face labor income shocks. Instead, they receive Social Security benefits that are a function of permanent income in the final period of working life. Let

$$\bar{z} = \exp(\kappa_{T_W} + z)$$

denote the level of last-working-period permanent income. Following Straub (2019), we model pre-tax Social Security income using the piecewise schedule

$$T^{SS}(\bar{z}; W) = 0.9 \min(\bar{z}, 0.2W) + 0.32 \left(\min(\bar{z}, 1.24W) - 0.2W\right)^+ + 0.15 \left(\min(\bar{z}, 2.47W) - 1.24W\right)^+,$$

where W denotes economy-wide average pre-tax labor income and $x^+ = \max\{x, 0\}$. Social Security income is then mapped through the same tax system,

$$\widetilde{T}^{SS}(\bar{z}; W) = \lambda \left[T^{SS}(\bar{z}; W)\right]^{1-\alpha}.$$

Once a household retires, $\bar{z}$ is fixed and retirement income remains constant over the remainder of life.

Value Functions. We next write the household's problem recursively. During working life, the value function for an age $t \leq T_W$ household with net worth b, permanent income z, transitory income ω, and employment status e is

$$V_t^W(b, z, \omega, e) = \max_{b' \geq \underline{B}} u(c) + \beta \, \mathbb{E}_{z', \omega', e'} \left[V_{t+1}^W(b', z', \omega', e') \right] \qquad \forall t < T_W,$$

subject to the budget constraint and mapping from income to ranks,

$$c + b' \leq b(1 + r_f) + \widetilde{w}_t(z, \omega, e), \qquad r = Rank_t(z, \omega, e),$$

and the laws of motion for permanent and transitory income,

$$z' = \begin{cases} z + \nu_{E,r,t+1} & \text{if } e' = E, \\ z + \nu_{N,r,t+1} & \text{if } e' = N, \end{cases} \qquad \omega' = \begin{cases} \omega_{r,t+1} & \text{if } e' = E, \\ 0 & \text{if } e' = N, \end{cases}$$

$$\nu_{e,r,t+1} \sim N(B_{e,r,t+1}, Q_{e,r,t+1}), \qquad \omega_{r,t+1} \sim N(0, R_{r,t+1}).$$

In the final period of working life, households make their consumption-savings decision and then enter retirement with frozen retirement income type $\bar{z}$. Their problem is therefore given by

$$V_{T_W}^W(b, z, \omega, e) = \max_{b' \geq \underline{B}} u(c) + \beta V_1^R(b', \bar{z})$$

subject to

$$c + b' \leq b(1 + r_f) + \widetilde{w}_{T_W}(z, \omega, e), \qquad \bar{z} = \exp(\kappa_{T_W} + z).$$

During retirement, there are no employment transitions and no further income risk. Letting $j \in \{1, \ldots, T_R\}$ index years since retirement, the value function for a retired household with net worth b and fixed retirement income type $\bar{z}$ is

$$\begin{aligned} V_j^R(b, \bar{z}) &= \max_{b' \geq \underline{B}} u(c) + \beta V_{j+1}^R(b', \bar{z}) \qquad \forall j < T_R, \\ V_{T_R+1}^R(b, \bar{z}) &= \phi(b), \end{aligned}$$

subject to

$$c + b' \leq b(1 + r_f) + \widetilde{T}^{SS}(\bar{z}; W).$$

4.1 Calibration

We next discuss the calibration of the model. Some parameters are assigned using estimates from the literature, while others are calibrated to be consistent with the U.S. labor and asset markets in the 1970s.

Demographics and Preferences. To align with the sample in Section 1.1, agents enter the model at age 25 ($t = 1$), work until age 60 ($T_W = 8$), and then retire from ages 65 to 95 ($T_R = 7$), with a model frequency of five years. When agents enter the model, they are employed and draw initial permanent income and initial assets jointly. We model this joint distribution using a Gaussian copula. The marginal distribution for permanent income is a normal distribution, and we estimate the standard deviation of this initial distribution as part of our estimation routine in Section 3. The marginal distribution of initial assets is a mixture. With probability p_{0,a_0} a household starts with zero assets; with probability $1 - p_{0,a_0}$ it draws positive assets from a log-normal distribution with parameters μ_{a_0} and σ_{a_0}. A correlation parameter ($\rho_{a_0 z}$) governs the dependence between the initial asset draw and the initial draw of permanent income. This formulation allows the model to match both the mass of households with little or no initial wealth and the substantial right tail in wealth among young households. We calibrate these parameters to match a series of moments from the asset distribution among 25-year olds in the 1970s SCF+. In particular, we calibrate the probability of zero initial assets (p_{0,a_0}) to match the share of individuals with negative assets at age 25. The mean and variance of the marginal distribution for assets are calibrated to match the mean of assets to income among 25-year olds, and the 95th percentile of assets to income, respectively. Finally, the copula correlation is calibrated to match the correlation of log income and log assets among 25-year olds.[50]

Agents receive utility from consumption and bequests, with preferences given by,

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}, \qquad \phi(b) = \kappa \frac{(b + \underline{b})^{1-\sigma}}{1-\sigma}.$$

We calibrate the preference parameters to match moments for assets to income over the age distribution as well as data on bequests. We calibrate the curvature on consumption and bequests

[50] In Appendix E.1, we show that the model is able to match the full distribution of assets to income among the young very well.

(σ) to match the ratio of average assets to income among 45-year olds.[51] The bequest multiplier (κ) is calibrated to match the ratio of assets to income among 55-year olds in the model.[52] The bequest intercept ($\underline{b}$) governs the degree to which bequests are a luxury good. As in De Nardi (2004), we calibrate this parameter to match the share of individuals who leave a bequest less than 6.5% of median income. Finally, the discount factor β is calibrated to match the savings rate of the top 10% of the income distribution from the 1970s SCF+, as reported in Mian et al. (2021b).

Income Process. In the model, agents receive a wage that is a function of their age, permanent and transitory income. The age component of income is estimated as part of the residualization process in Section 2.

When agents are non-employed/non-filing they receive (pre-tax and transfers) a fraction $\gamma \in [0, 1]$ of their age-profile income. The parameter γ can be thought of as the replacement rate of unemployment insurance. As in Shimer (2005), we set $\gamma = 0.4$. Upon retirement, households no longer face labor income shocks and instead receive Social Security benefits according to $T^{SS}(\bar{z}; W)$, where benefits depend on permanent income in the last period of working life and are held fixed throughout retirement.

Shocks to Income. Within the model, we implement our estimates of the income process described in Section 2. In this model, conditional distributions of shocks for agents in a given period depend on their within-age income rank in the prior period for all periods other than the first period of their life. The sequential exogeneity timing, in addition to the fact that ranks are within-age, make the steady-state ranks of income as a function of permanent and transitory income easy to compute outside of all equilibrium conditions.[53] Hence, before VFI and market clearing are computed, the $Rank_t(z, \omega, e)$ function can be computed, and hence conditional expectations within VFI are straightforwardly taken.

[51]In our baseline estimation, we set the curvature on bequests and consumption to be the same. In Appendix E.4, we show that we obtain very similar results for our main quantitative experiment in a version of our model where we set the curvature on bequests to be lower than the curvature on consumption.

[52]In Appendix E.1, we show the quantitative model's profile of assets to income over the entire working lifecycle and compare these estimates to the data.

[53]Specifically, a large number of agents can be initialized at age 25. Then, income can be ranked within age-25 agents, and distributions of age-30 permanent and transitory income computed for each agent given their age-25 ranks. The agents can then be simulated forward to age 30, ranked within age-30 agents, distributions of age-35 permanent and transitory income computed, and simulated forwards again to age 35. This process is repeated until all agents reach age 60. Then, for any permanent and transitory income level at any age, the level of income can be computed and the rank determined.

Probability of Non-Employment. Similar to Braxton et al. (2025), we model the likelihood that an employed individual becomes non-employed/non-filing as a non-linear function of prior income rank r. In particular, we use the parameter estimates from estimating equation (6) to specify the following non-linear probability of being non-employed/non-filing based on prior income rank for those who are currently employed,

$$p(N|r, E) = \alpha_0 + \alpha_1 r + \alpha_2 r^2 + \alpha_3 r^3. \tag{6}$$

We include the parameters $\{\alpha_k\}_{k=0}^{3}$ in Table 3. The parameter estimates imply that the probability of transitioning from employed to non-employed/non-filer is a decreasing function of prior income rank. We model the probability of remaining non-employed/non-filing if an individual is currently in that state to be a constant, i.e. $p(N|r, N) = \alpha_N$. We find that the share of individuals remaining in this state across 5-year observations is 26.2%.

Taxes. We use a progressive tax function as in Benabou (2002) and Heathcote et al. (2017). We set the tax progressivity parameter α equal to 0.181 based on the estimates in Heathcote et al. (2017), and set the location parameter λ equal to 5.620. Based on our parameterized tax function, agents with pre-tax incomes below approximately \$10K receive transfers from the government, while individuals with pre-tax incomes greater than \$10K pay labor income taxes. In our model, the average tax rate for agents above the 20th percentile of the income distribution is 21.6%, close to the estimate of 20.5% for the U.S. in the 1970s from Piketty and Saez (2007). We apply the same tax mapping to Social Security income in retirement.

Asset Markets. Agents are able to save and borrow at the annualized risk-free rate of 3.5%, which is the average value of the risk-free rate in the 1970s as measured by Laubach and Williams (2003). This interest rate results in assets being in positive net supply, and in the interest rate experiment in Section 5, we hold this level of assets fixed and adjust the equilibrium interest rate to clear the asset market. We set the borrowing limit $\underline{B}$ to the natural borrowing limit.[54]

Table 3 presents the parameters that govern the model economy, while Table 4 shows the model fit of the calibrated parameters. The model matches the calibrated moments very well. We next discuss a series of non-targeted moments, which serve as a model validation exercise.

[54] In our model, implementing the natural borrowing limit is equivalent to requiring that individuals die with zero debt.

Table 3: Model Parameters

Non-calibrated Parameters		
Variable	Value	Description
r_f	3.50%	Annual risk-free interest rate
α	0.181	Progressivity of tax function
λ	5.620	Location parameter of tax function
γ	0.400	Replacement rate UI
α_N	0.262	Unemployed/nonfiler rate for unemployed/nonfiler
α_0	0.178	Added constant in unemployment probability for employed
α_1	-0.00441	Linear term in unemployment probability for employed
α_2	4.71×10^{-5}	Square term in unemployment probability for employed
α_3	-1.41×10^{-7}	Cube term in unemployment probability for employed
Calibrated Parameters		
Variable	Value	Description
β	0.743	Discount factor
σ	3.124	Risk aversion
κ	102.456	Bequest strength
$\underline{b}$	90,098	Bequest lower bound
σ_{a_0}	58,547	Standard deviation of initial asset draw
μ_{a_0}	12,992	Mean of initial asset draw
p_{0,a_0}	0.476	Probability of zero initial assets
$\rho_{a_0 z}$	0.300	Correlation between initial assets and income

Note: Table presents model parameters for the baseline estimation of the quantitative model.

4.2 Non-targeted Moments

In this section, we present a set of non-targeted moments that serve as a model validation exercise. Using model simulated data, we examine how savings responds to changes in permanent and transitory income risk. For this experiment, we solve and simulate data from a set of model economies where we perturb the income process around its baseline estimation.[55] We then combine the simulated data from each perturbation and estimate equation 5, following the same empirical specification used in the data.[56] Figure 10 presents the results.

[55]We perform 36 perturbations of the income process. Each perturbation is a vector of five additive shifters $\vec{x} = (x_1, \ldots, x_5)$, one for each income-process parameter $B_E + x_1$, $B_N + x_2$, $Q_E + x_3$, $Q_N + x_4$, and $R + x_5$. The shifters $\vec{x}$ are drawn from a 36 point Sobol sequence over 5 dimensions, with identical boundaries on each dimension of $[-0.02, 0.05]$. Results are similar when varying both the number of perturbations and the interval over which the perturbations are drawn.

[56]Because the model produces a full simulated panel, we can include lagged income-rank, lagged wealth-centile, and age fixed effects in the model regressions. Since we perturb the full income profile, we additionally control for the mean shock to permanent income both while employed and non-employed in all specifications.

Table 4: Calibrated Parameters

Parameter	Value	Moment	Data	Model
β	0.743	Savings Rate, Top 10% of Income Distribution	0.253	0.199
σ	3.124	Mean Assets to Income, Age 45	2.894	3.000
κ	102.456	Mean Assets to Income, Age 55	4.702	4.908
$\underline{b}$	90,098	Bequests Less than 6.5pct of Median Income	0.300	0.445
σ_{a_0}	58,547	P95 Assets to Income, Age 25	3.227	3.283
μ_{a_0}	12,992	Mean Assets to Income, Age 25	1.094	1.079
p_{0,a_0}	0.476	Share Negative Assets, Age 25	0.235	0.314
$\rho_{a_0 z}$	0.300	Correlation Log Assets and Log Income, Age 25	0.332	0.475

Note: Table presents fitted parameters and targeted data moments.

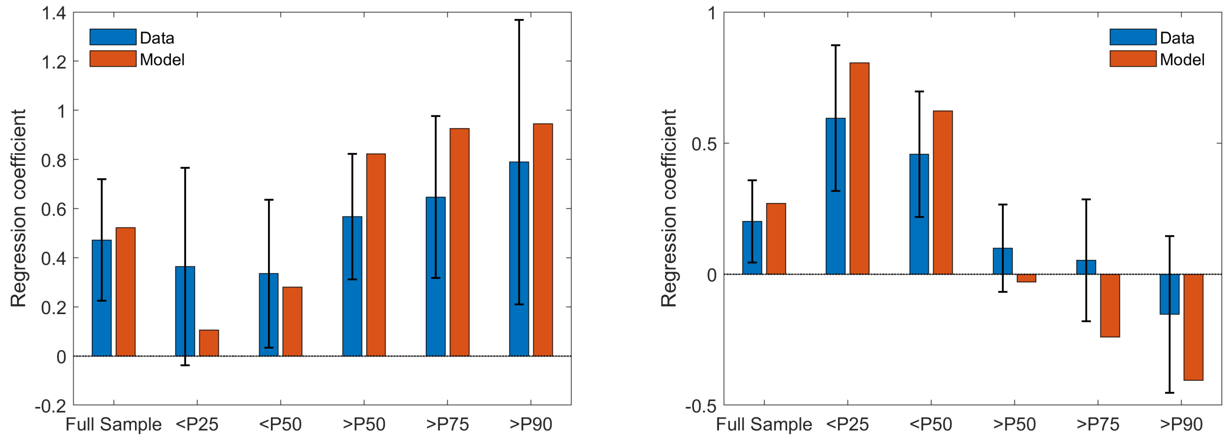
Panel (a) examines the savings response to permanent income risk in the full sample and across income-rank subsamples. The leftmost bars show that, in the full sample, the model predicts that a 0.1 increase in the variance of permanent income shocks increases wealth by 5.2% of prior income. The corresponding estimate in the data is 4.7%, as shown in Section 3.3. Thus, the model generates a savings response to permanent income risk that is close to our empirical estimate. The figure also shows that the model is able to generate the empirical pattern that the savings response to an increase in permanent income risk is larger among higher-income households.

Panel (b) examines the savings response to transitory income risk. In the full sample, the model predicts that a 0.1 increase in the variance of transitory shocks increases wealth by 2.69% of prior income. This response is smaller than the response to permanent risk and close to the empirical estimate of 1.94%. The model also captures the broad empirical pattern that the savings response to transitory risk is larger among lower-income households and smaller among higher-income households.

Taken together, Figure 10 shows that the quantitative model captures the savings responses to permanent and transitory income risk, as well as the income gradients in these responses. The model predicts that permanent income risk generates especially large savings responses among high-income households, while transitory income risk generates larger responses among lower-income households. In Appendix E.2, we show that the model also largely captures how these savings responses vary over the life cycle. We next examine how the shape of the income risk profiles affects savings behavior in the quantitative model.

Figure 10: Savings Response to Permanent & Transitory Income Risk: Model and Data

(a) Permanent Risk (b) Transitory Risk



Note: The figure shows the savings response to permanent (panel (a)) and transitory (panel (b)) income risk in the quantitative model and in the data. Model based estimates are given by the orange bars, while the data estimates are represented by the blue bars. The full-sample estimates use all agents; the remaining estimates are estimated separately by lagged income-rank subsample. Error bars denote 99% confidence intervals for the data estimates.

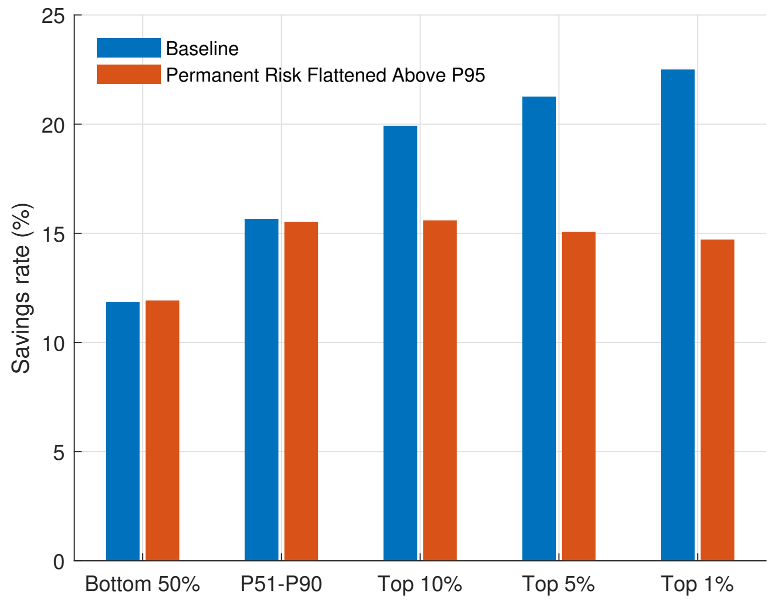
4.3 Mechanisms: The Impact of Convex Permanent Income Risk

A central finding of our empirical analysis is that permanent income risk rises steeply in the right tail of the income distribution, a feature we refer to as *convex permanent income risk*. In this section, we examine how this feature affects savings behavior at the top of the income distribution and contributes to wealth concentration. To isolate the role of convex permanent income risk, we compare the baseline model to a counterfactual economy in which the profile of permanent income risk is flattened above the 95th percentile. In particular, for households above the 95th percentile of the lagged earnings distribution, we set Q_E, the permanent income risk of employed households, equal to its value at the 95th percentile.[57]

We first examine the degree to which convex income risk affects savings behavior. Figure 11 compares savings rates across the income distribution in the baseline economy (blue bars) and in the counterfactual economy in which permanent income risk is flattened at the 95th percentile (orange bars). The baseline model generates a steep income gradient in savings rates,

[57] In Appendix E.3, we present the full profiles of income risk in the baseline model and in the model with income risk flattened at the 95th percentile. Flattening permanent income risk at the 95th percentile substantially reduces permanent income risk at the top of the distribution. For example, at age 30 the variance of shocks to permanent income at the 95th percentile is 0.10, while at the 98th percentile it is nearly 0.15 and for the top percentile it is 0.29.

Figure 11: Convex Permanent Income Risk and Savings



Note: The figure compares savings rates across the income distribution in the baseline economy and in the counterfactual economy in which permanent income risk is flattened above the 95th percentile. In the counterfactual, the permanent income risk of employed households, Q_E, is held fixed at its 95th percentile value for all households above the 95th percentile of the lagged earnings distribution.

consistent with prior evidence that high-income households save at higher rates (e.g., Carroll (2000), Dynan et al. (2004), Straub (2019), Mian et al. (2020), among others). Flattening permanent income risk above the 95th percentile leaves savings rates essentially unchanged below the top decile, but substantially reduces savings at the top. The savings rate of the top 5% falls from over 21% to 15%, and the savings rate of the top 1% falls from 22.5% to less than 15%. Thus, convex permanent income risk plays a central role in the steep increase in savings rates at the top of the income distribution.

We next examine the implications for wealth concentration. Table 5 reports wealth shares in the 1970s U.S. data, the baseline model, and the counterfactual economy in which permanent income risk is flattened above the 95th percentile. The baseline model understates wealth concentration relative to the data, but nevertheless generates substantial concentration. In the baseline model, the top 10% hold 42.6% of aggregate wealth, and the top 1% hold 11.5%. Flattening permanent income risk above the 95th percentile reduces wealth concentration at the top of the distribution. The top 1% wealth share falls from 11.5% to 9.6%, while the top 5% and top 10% shares fall by 2.3 and 2.0 percentage points, respectively.

The results of this section show that convex permanent income risk is an important force behind high savings rates at the top of the income distribution and contributes meaningfully to

Table 5: Convex Permanent Income Risk and Wealth Concentration

Wealth Share	Data (1970s)	Baseline Model	Flattening Q_E Above P95
Top 10%	52.7%	42.6%	40.6%
Top 5%	39.1%	29.0%	26.7%
Top 1%	18.9%	11.5%	9.6%

Note: The table reports the share of wealth held by the top of the wealth distribution in the 1970s U.S. data and in the model. Column (1) reports wealth shares from the Survey of Consumer Finances. Column (2) reports the baseline model. Column (3) reports the counterfactual economy in which permanent income risk is flattened above the 95th percentile: for households above the 95th percentile of the lagged earnings distribution, the permanent income risk of employed households, Q_E, is held fixed at its 95th percentile value.

wealth concentration. Next, we examine how changes in these profiles over time have affected macroeconomic aggregates.

5 Implications of Rising Income Risk

In this section, we examine how changes in income risk across the distribution have impacted the risk-free rate and wealth inequality. In this experiment, we change the parameters of the income process from the baseline 1970s estimates to the 2010s estimates, and then we solve for the risk-free rate that maintains the same positive level of net asset supply as the baseline economy.[58] Table 6 presents the results of this experiment.

We start by considering changes in all parameters of the income process between the 2010s and the 1970s. To understand the effect of the changes in the income process on agents in the model, we first examine how savings behavior changes in Panel (a) of Figure 12. The blue bars show that in the baseline version of the model, high-income households have higher saving rates. As we move to the 2010s, income risk rises across the distribution. In partial equilibrium, this increase in risk would raise desired precautionary savings for all households. In general equilibrium, however, the asset market clears through a decline in the risk-free rate, which weakens incentives to save. The orange bars in panel (a) of Figure 12 show that, in equilibrium, households below the top decile reduce their saving rates relative to the 1970s, while households in the top decile increase their savings sharply. Thus, for most households the decline in the interest rate more than offsets the increase in precautionary saving motives, whereas for top-income households the rise in income risk is strong enough to dominate the equilibrium price effect. Our model therefore predicts that rising income risk increases savings at the top

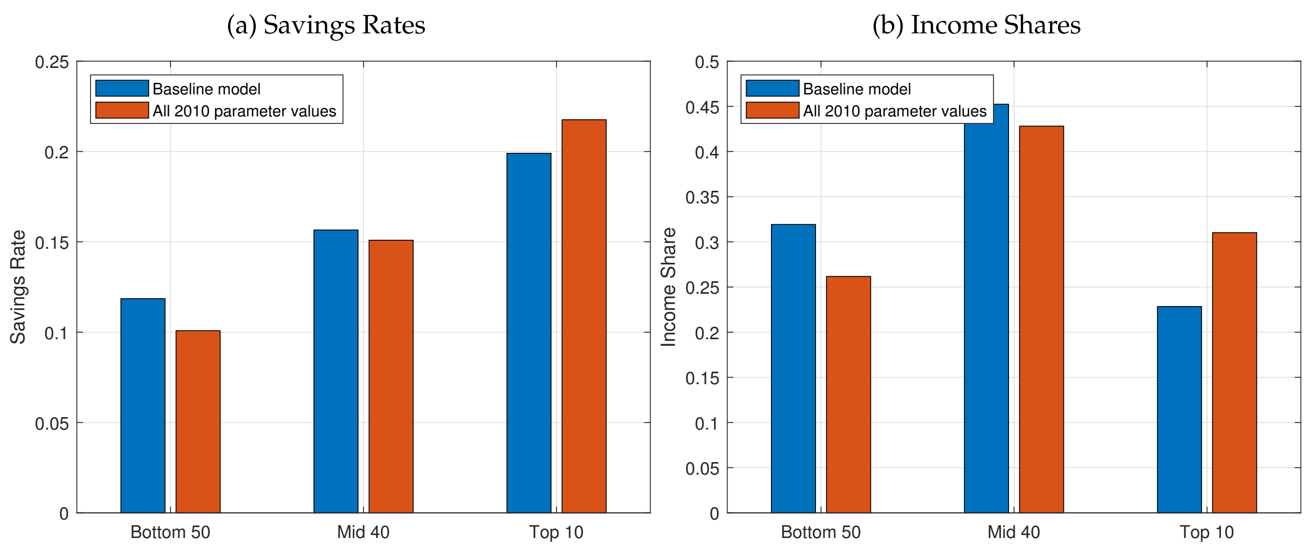
[58] Additionally, to highlight the changes in risk (and not changes in mean income due to Jensen's inequality), we adjust the age income profile to keep the level of average income fixed across the estimations of the model.

Table 6: Impact of Changes in Income Risk on Interest Rates and Wealth Inequality

Economy	(1) Baseline (1970s)	(2) 2010s	(3) $\Delta_t Q_E$	(4) $\Delta_t R$	(5) $\Delta_t B$
Counterfactual alters		All Parameters	Perm. Income Risk Emp.	Temp. Income Risk	Perm. Income Means
Risk-free rate	3.50%	2.80%	3.00%	3.48%	3.35%
Top 10% Wealth Share	42.60%	50.11%	46.08%	42.65%	45.67%
Top 5% Wealth Share	28.98%	36.59%	32.50%	29.06%	31.85%
Top 1% Wealth Share	11.50%	16.60%	14.14%	11.68%	13.15%
Top 0.1% Wealth Share	2.93%	4.26%	3.71%	2.96%	3.27%

Note: Table presents the results of changing income risk across the distribution between the 1970s and 2010s on the risk-free rate and measures of wealth inequality. The first column corresponds to our 1970s estimation of the model. In column (2) we adjust all income process parameters to their 2010s values. In columns (3)-(5), we adjust a component of the income process parameters.

Figure 12: Changes in Savings Behavior and Income Shares Across the Income Distribution



Note: The figure compares savings rates (panel (a)) and income shares (panel (b)) across the income distribution in the 1970s baseline economy (blue bars) and the 2010s economy (orange bars). In each figure the left-hand set of bars correspond to individuals in the bottom 50% of the income distribution, the middle bar corresponds to households between the 50th and 90th percentiles, which we refer to as "Mid 40" and the right-hand side bar corresponds to the top 10% of the income distribution.

of the income distribution while reducing saving rates for the rest of the distribution, a pattern that is consistent with the recent empirical evidence in Mian et al. (2020) on the "savings glut of the rich."

We find that the risk-free rate declines to 2.8% to balance the supply and demand of savings (column (2) of Table 6). Thus, changes in the income process have led to a substantial decline in the risk-free rate over the prior 40 years. Given that Laubach and Williams (2003) estimate that the average real interest rate has declined by approximately 2.5pp between the 1970s and 2010s, we conclude that structural changes in income process dynamics can account for nearly 30% of the fall in real interest rates over the 1970-2019 period (see Table 8).[59]

We additionally examine how changes in the income process impact wealth inequality. There are two channels through which the changes in the income process impact wealth inequality. First, as discussed above, high income households increase their savings rate. Second, the changes in our income process, where high income households have seen an increase in permanent income risk and in the mean shock to permanent income, results in the top 10% of the income distribution holding a larger share of earnings.[60] Panel (b) of Figure 12 shows that the share of income going to the top 10% of the income distribution increases by approximately 8 percentage points. Given that high income households hold a larger share of income and save a larger fraction of it, wealth concentration at the top increases. In Table 6, we examine wealth inequality by tracking the share of wealth held by the top 10%, 5%, 1% and 0.1% of the distribution. We find that the changes in the income process have led to an increase in wealth concentration according to all of these measures. In particular, we find that the top 1% wealth share has increased by over 5pp, and the top 0.1% wealth share has increased by over 1.3pp (column (2) of Table 6). Thus, our documented changes in the profile of income risk have reduced interest rates and expanded wealth inequality.[61]

We next examine which components of the change in income risk is driving the decline in the risk-free as well as the increase in wealth inequality. We first consider how the increase in permanent risk among the employed impacts savings behavior and the risk-free rate. Panel (b) of Figure 4 presents the profile of shocks to permanent income among the employed across the income distribution in the 1970s economy (black, solid line) and the 2010s economy (red, dashed line). In response to the increase in permanent risk at the top of the distribution, saving increases, and the risk-free rate declines substantially. In column (3) of Table 6, we show that to clear the asset market following the rise in permanent risk, the risk-free rate must decline to

[59]We use the updated Laubach and Williams (2003) time series for R-star maintained by the Federal Reserve Bank of New York: `https://www.newyorkfed.org/research/policy/rstar`.

[60]Note that in these experiments we adjust the age earnings profile so that mean earnings are equal across model comparisons. However, the average level of income by lagged rank can change across these estimations due to changes in the income process parameters.

[61]In Appendix E.4, we show that the decline in the risk-free rate has further amplified the increase in wealth inequality because as interest rates have declined low income households have cut their savings below their 1970s levels.

Table 7: Impact of Changes Among Top Earners on Interest Rates and Wealth Inequality

Economy	(1) Baseline (1970*s*)	(2) 2010*s*	(3) 2010*s*, p90+	(4) 2010*s*, p95+
Counterfactual alters		All Parameters	All Parameters, p90–p100 only	All Parameters, p95–p100 only
Risk-free rate	3.50%	2.80%	3.275%	3.325%
Top 10% Wealth Share	42.60%	50.11%	48.48%	47.13%
Top 5% Wealth Share	28.98%	36.59%	35.51%	34.10%
Top 1% Wealth Share	11.50%	16.60%	16.39%	16.07%
Top 0.1% Wealth Share	2.93%	4.26%	4.22%	4.22%
Share of full change:				
Risk-free rate	—	100%	32%	25%
Top 1% Wealth Share	—	100%	96%	90%

Note: Table presents the results of quantitative experiments in which income process parameters evolve from their 1970s to their 2010s values only for earners at or above the indicated percentile of the income distribution; parameters for all other percentiles are held at their 1970s values. Columns (1) and (2) repeat the baseline and 2010s counterfactual from Table 6. Columns (3) and (4) restrict the change to p90–p100 and p95–p100, respectively. The bottom panel expresses each column's change relative to the full change in column (2).

3%, 0.5pp lower than its 1970s value. Thus, increases in permanent income risk at the top of the distribution play a substantial role in decreasing the risk-free rate between the 1970s and the 2010s. Additionally, with higher income households saving more, wealth inequality expands. The change in permanent income profiles increase the top 1% wealth share by over 2.5pp.

In column (4) of Table 6, we examine the impact of changes in transitory income risk. We find that the change in transitory income risk has had virtually no effect on the risk-free rate and wealth inequality. The reason is that although high income households have seen an increase in transitory risk, they do not increase their savings in response to it. Additionally, the changes in transitory income risk do not have a meaningful impact on the share of income held across the distribution.

Finally, we examine the role of changes in the mean shock to permanent income. We find that the changes in the mean shock to permanent income have led to a small decline in the risk-free rate, as well as an expansion of wealth concentration at the top. The reason is that the changes in the mean shock to permanent income have contributed to the increase in the income share of the top 10%. Since these households have higher savings rates, when they hold more income, aggregate savings increases. With the increase in aggregate savings from these households, there is downward pressure on interest rates, while wealth inequality expands.

Isolating the Role of Top Earners. To isolate the contribution of changes in the income process among top earners, we repeat the previous exercise but allow income process parameters to evolve to their 2010s values only for earners at or above the 90th percentile of the income distribution. For all other percentiles, the income process is held fixed at its 1970s values. Column (3) of Table 7 reports the results. This change lowers the equilibrium risk-free rate to 3.275%, accounting for roughly one-third of the model's total decline in the risk-free rate over this period. This experiment also produces most of the rise in wealth concentration generated by the full 2010s income process, particularly at the very top of the wealth distribution. For example, the top 1% wealth share rises from 11.50% in the baseline economy to 16.39% when only changing the income process above the 90th percentile, compared with 16.60% in the full 2010s counterfactual. In column (4), we extend the exercise by allowing only the income process parameters of earners at or above the 95th percentile to change. The results show that the upper tail alone matters quantitatively: changing the income process only above the 95th percentile explains one-quarter of the decline in the risk-free rate and nearly all of the rise in top wealth concentration.

Summary of Quantitative Findings. Table 8 summarizes the headline effects of income risk on wealth inequality and interest rates and how they compare to changes observed in the data.

Rising risk explains an economically meaningful share of the observed rise in wealth concentration. From the 1970s to 2010s, the wealth share of the top 1% increased by 11.5 percentage points in the SCF+. Changing all income process parameters yields a 5.1 percentage point increase in top 1% wealth shares, accounting for 44.3% of the increase observed in the data. Changes in income risk among the top earners (p95+) alone explains 39.7% of the increase in top 1% wealth shares observed in the data.

Rising risk also has economically meaningful implications for interest rates. According to updated time series from Laubach and Williams (2003), real rates fell by 2.5 percentage points from the 1970s to 2010s. Similar patterns appear in 10-year real rates and total returns to wealth (e.g., Auclert et al. (2021)). Changing all income process parameters yields a 0.7 percentage point decrease in the risk-free rate, accounting for 27.7% of the decrease observed in the data. Changes in income risk among the top earners (p95+) alone explains 6.9% of the decline in the risk-free rate in the data.

Taken together, these results indicate that changes to the income process at the top of the earnings distribution play a central role in rising wealth concentration and a moderate role in declining interest rates, while broader changes to the full profile of income risk play a central role in declining interest rates.

Table 8: Model vs. Data: Top 1% Wealth Share and Risk-Free Rate

	Top 1% Wealth Share			Risk-free Rate		
	Data	Model (full)	Model (p95–p100 only)	Data	Model (full)	Model (p95–p100 only)
1970s	18.9%	11.5%	11.5%	3.5%	3.5%	3.5%
2010s	30.4%	16.6%	16.1%	1.0%	2.8%	3.3%
Change (pp)	11.5	5.1	4.6	−2.5	−0.7	−0.2
Percent explained by model		44.3%	39.7%		27.7%	6.9%

Note: Table summarizes the results of quantitative experiments from Table 6 and Table 7. Top 1% wealth share data comes from SCF+. The risk-free rate data is from the updated version of Laubach and Williams (2003), pulled in September 2025. Model (full) corresponds to the experiment in which all income process parameters evolve from their 1970s to their 2010s values. Model (p95–p100 only) reports the results in which we restrict the change to p95–p100. The bottom row expresses the model change over the data change from 1970s to 2010s.

6 Conclusion

This paper revisits the evolution of income risk in the United States and studies its implications for saving behavior, interest rates, and wealth inequality. Using a newly available panel of household income from the universe of U.S. tax returns, we document that permanent income risk has risen substantially since the 1970s, with especially large increases at the top of the income distribution.

We provide several pieces of evidence that high income households face substantial income risk. The permanent income shocks recovered from our income process are associated with observable measures of economic distress and adjustment, including early retirement-account withdrawals and moves to lower-income ZIP codes, even among households at the very top of the income distribution. We then show that these differences in permanent income risk are relevant for saving behavior. Using capitalized interest and dividend income to construct proxies for wealth and saving, we find that households with greater exposure to permanent income risk save more, with the strongest responses among younger and high-income households.

Finally, we study the aggregate implications of these changes in a quantitative life-cycle model. The model shows that the rise in permanent income risk at the top of the distribution increases saving among high-income households, lowers the equilibrium risk-free rate, and raises wealth concentration. These forces generate a "savings glut of the rich": saving rises sharply at the top even as lower interest rates dampen saving incentives for much of the rest of the distribution. Taken together, our results suggest that the evolution of income risk among top earners is central to understanding both household saving behavior and aggregate trends in interest rates and wealth inequality.

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A Additional details: Estimation

In this appendix, we provide a series of additional details and results for our estimation routine. We first provide additional details about the Kalman Filtering Step of the estimation in Appendix A.1.

A.1 Kalman Filter

Our derivations of the Kalman filter and smoother are primarily based on Hamilton (1994). For convenience in computing parameter updates in the EM algorithm, we modify equation (2) so that the state variable includes both the current realization of permanent income and its lag. Let $\zeta_{i,t}$ denote a household i's unobserved state in period t:

$$\zeta_{i,t} = \begin{bmatrix} z_{i,t} \\ z_{i,t-1} \end{bmatrix},$$

For casting the income process from equations (1)-(3) into state-space form, we make the following adjustments to notation to facilitate running the Kalman filter for each household i. We let $B_t(l_{i,t}, r_{i,t-1})$ denote the drift for a household i in period t who has employment status $l_{i,t}$ and has prior rank $r_{i,t-1}$. We analogously define $R_t(l_{i,t}, r_{i,t-1})$ and $Q_t(l_{i,t}, r_{i,t-1})$.

State equation. From equation (2), the law of motion for the state vector $\zeta_{i,t}$ (i.e., the *state equation*) can be rewritten as,

$$\zeta_{i,t} = \begin{bmatrix} z_{i,t} \\ z_{i,t-1} \end{bmatrix} = \underbrace{\begin{bmatrix} B_t(l_{i,t}, r_{i,t-1}) \\ 0 \end{bmatrix}}_{\widehat{B}_t(l_{i,t}, r_{i,t-1})} + \underbrace{\begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}}_{\widehat{F}} \zeta_{i,t-1} + \begin{bmatrix} \nu_{i,t} \\ 0 \end{bmatrix}. \tag{7}$$

Measurement equation. Using the definition of the state vector $\zeta_{i,t}$, the law of motion for income in equation (1) can be rewritten using an observation matrix $H(l_{i,t})$, where $H(l_{i,t}) = \begin{bmatrix} l_{E,i,t} & 0 \end{bmatrix}$ governs the relationship between the state vector $(\zeta_{i,t})$ and income $y_{i,t}$ among households who are employed $(l_{E,i,t} = 1)$.[62] The resulting law of motion is our *measurement equation*,

$$y_{i,t} = H(l_{i,t})\zeta_{i,t} + l_{E,i,t}\,\omega_{i,t}, \tag{8}$$

[62] When a household is non-employed/non-filing ($l_{E,i,t} = 0$), the observation $y_{i,t}$ provides no signal about latent income other than what can be inferred from other observables. In those instances, the Kalman filter does not use $y_{i,t}$ to update its guess about $z_{i,t}$. $H(l_{i,t})$ captures that intuition.

We apply the Kalman filter and smoother to the state-space system defined by equations (7) and (8). In the Kalman filtering step of the estimation, we assume the parameters of the income process are known. In the EM step of our estimation routine, which we discuss in Appendix A.2, we estimate the parameters that govern the income process. Starting with estimates $\widehat{\zeta}_{i,1|0}$ and $M_{i,1|0}$, which we will define below, we obtain an estimate of the time series of permanent income (and its lag) from the Kalman filter, which we denote $\widehat{\zeta}_{i,t|t}$, as follows:[63]

1. Estimate the Kalman Gain:

$$K_{i,t} = M_{i,t|t-1}H^{'}(l_{i,t})\left[H(l_{i,t})M_{i,t|t-1}H^{'}(l_{i,t}) + R_t(l_{i,t}, r_{i,t-1})\right]^{-1}.$$

2. Update the state vector:

$$\widehat{\zeta}_{i,t|t} = \widehat{\zeta}_{i,t|t-1} + K_{i,t}\left(y_{i,t} - H(l_{i,t})\widehat{\zeta}_{i,t|t-1}\right)$$
$$\widehat{\zeta}_{i,t+1|t} = \widehat{F}\widehat{\zeta}_{i,t|t} + \widehat{B}_{t+1}(l_{i,t+1}, r_{i,t}).$$

3. Update the MSE matrix:

$$\begin{aligned} M_{i,t|t} &= M_{i,t|t-1} - K_{i,t}H(l_{i,t})M_{i,t|t-1} \\ M_{i,t+1|t} &= \widehat{F}M_{i,t|t}\widehat{F}' + Q_{t+1}(l_{i,t+1}, r_{i,t})e_1^2 e_1^{2'}. \end{aligned}$$

where $e_1^2 = [1, 0]'$. Repeat steps 1-3 for $t = 2, ...T$, and for each household $i \in \{1, .., N\}$. Finally, to run the Kalman filter we need an estimate of the mean of the state-vector ($\widehat{\zeta}_{i,1|0}$) and the MSE matrix ($M_{i,1|0}$). When a household enters into the labor market, we set their lagged rank to zero and thus we set $\widehat{\zeta}_{i,1|0} = \widehat{B}_1(l_{i,1}, 0)$, and we initialize the variance of the state vector using,[64]

$$M_{i,1|0} = \begin{bmatrix} Q_0 + Q(l_{i,1}, 0) & Q_0 \\ Q_0 & Q_0 \end{bmatrix}.$$

Kalman Smoother In order to apply the EM algorithm below, we must apply the Kalman smoother after running the Kalman filter. We denote the resulting posterior estimates from running the Kalman smoother step as $\{\{\widehat{\zeta}_{i,t|T}\}_{t=0}^T\}_{i=1}^N$ and $\{\{M_{i,t|T}\}_{t=0}^T\}_{i=1}^N$. The steps for the smoothed Kalman filter are:

[63] We use $\widehat{\zeta}_{i,t|t-1}$ to denote the estimate of permanent income for household i in period t using data through period $t-1$. Similarly, we let $M_{i,t|t-1}$ denote the uncertainty in this estimate.

[64] For a households first observation in the labor market, we need to specify a rank for drawing their permanent and transitory shock. We give them a "rank" of zero. Our results are robust to this choice.

1. Run the Kalman filter as presented above storing the sequences $\{M_{i,t|t-1}\}_{t=1}^{T}$ and $\{M_{i,t|t}\}_{t=1}^{T}$ as well as $\{\hat{\zeta}_{i,t|t-1}\}_{t=1}^{T}$ and $\{\hat{\zeta}_{i,t|t}\}_{t=1}^{T}$.

2. Store the element $\hat{\zeta}_{i,T|T}$ from $\{\hat{\zeta}_{i,t|t}\}_{t=1}^{T}$.

3. Calculate the sequence of smoothed estimations $\{\hat{\zeta}_{i,t|T}\}_{t=1}^{T-1}$ in reverse order by iterating on:

$$\hat{\zeta}_{i,t|T} = \hat{\zeta}_{i,t|t} + J_{i,t}(\hat{\zeta}_{i,t+1|T} - \hat{\zeta}_{i,t+1|t})$$

   for $t = T-1, T-2, ..., 1$, where $J_{i,t} = M_{i,t|t}\hat{F}' M_{i,t+1|t}^{-1}$.

4. Update the sequence of MSE by iterating on:

$$M_{i,t|T} = M_{i,t|t} + J_{i,t}(M_{i,t+1|T} - M_{i,t+1|t})J_{i,t}'.$$

A.2 Expectation Maximization (EM) Algorithm.

In this appendix we discuss how we use an EM algorithm to tractably update the parameters of our income process. To derive the EM updating formulas, the first step is to write down the full-information log likelihood assuming that state-variables (i.e., $z_{i,t}$) are observed:

$$\begin{aligned} LL_i(\{y_{i,t}\}_{t=1}^{T}, \{z_{i,t}\}_{t=1}^{T} \mid \{l_{i,t}\}_{t=1}^{T}, \theta_0) = &-\frac{T+1}{2}\log(2\pi) \\ &-\frac{1}{2}\log(Q_0) - \frac{1}{2}\frac{(z_{i,0})^2}{Q_0} \\ &-\frac{1}{2}\sum_{t=1}^{T}\log(Q_t(l_{i,t}, r_{i,t-1})) - \frac{1}{2}\sum_{t=1}^{T}\frac{(z_{i,t} - z_{i,t-1} - B_t(l_{i,t}, r_{i,t-1}))^2}{Q_t(l_{i,t}, r_{i,t-1})} \\ &-\frac{1}{2}\sum_{t=1}^{T}\log(R_t(l_{i,t}, r_{i,t-1})) - \frac{1}{2}\sum_{t=1}^{T}\frac{(l_{E,i,t})(y_{i,t} - z_{i,t})^2}{R_t(l_{i,t}, r_{i,t-1})}, \end{aligned} \tag{9}$$

where the parameter vector is denoted $\theta_0 = \{Q_t(\cdot), R_t(\cdot), B_t(\cdot), Q_0\}$.

E-Step. The second step is to take the expectation of the likelihood with respect to $\{z_{i,t}\}$, given $\{y_{i,t}\}_{t=1}^{T}$:

$$\mathcal{L}(\theta_0) = E_{\{z_{i,t}\}_{t=1}^{T}}\left[LL_i(\{y_{i,t}\}_{t=1}^{T}, \{z_{i,t}\}_{t=1}^{T} \mid \{l_{i,t}\}_{t=1}^{T}, \theta_0)\Big|\{y_{i,t}\}_{t=1}^{T}\right]$$

This amounts to integrating equation (9) with respect to the distribution of the latent states $F(\{z_{i,t}\} \mid \{l_{i,t}, y_{i,t}\}_{t=1}^{T}, \theta_0)$ to express the likelihood in terms of posterior means and covariances.

The Kalman filter yields $F(\{z_{i,t}\} \mid \{l_{i,t}, y_{i,t}\}_{t=1}^{T}, \theta_0)$, making this integration simple.

Why is the integration with respect to z simple? Shumway and Stoffer (1982) show, this expectation yields the likelihood function in terms of $\{\widehat{\zeta}_{i,t|T}\}_{t=1}^{T}$ and $\{M_{i,t|T}\}_{t=1}^{T}$, both of which are estimated by the Kalman filter and smoother.[65] In other words, when we take the expectation of the likelihood given observed data $\{y_{i,t}\}_{t=1}^{T}$, the unobserved latent states $z_{i,t}$ become simple posteriors from the Kalman filter, $\widehat{z}_{i,t|T} = E[z_{i,t} \mid \{l_{i,t}, y_{i,t}\}_{t=1}^{T}, \theta_0]$, and covariances are given by $\{M_{i,t|T}\}_{t=1}^{T}$.

M-step. The third and final step is to take first order conditions of $\mathcal{L}(\cdot)$ with respect to the income process parameter vector, θ_0.[66] Consider the drift $B_t(\cdot)$. One may intuit from the quadratic functional form of the log likelihood that the resulting first order conditions will resemble ordinary least squares regressions formulas. The intuition is correct, except the updating formulas are generalized least squares regression formulas with weights that adjust for filtering uncertainty. The intuition comes from taking the expectation of equation (2) with respect to $\{z_{i,t}\}$, given $\{y_{i,t}\}_{t=1}^{T}$, which naturally suggests that B can be updated via regression:

$$\widehat{z}_{i,t|T} = \widehat{z}_{i,t-1|T} + B_t(l_{i,t}, r_{i,t-1})$$

We update the variances by taking the first order condition of $\mathcal{L}(\cdot)$ with respect to $Q_t(\cdot)$ and $R_t(\cdot)$, and then solving the first order conditions via Newton's method. We restrict the variance terms to be log-linear in parameters, yielding a well-defined concave optimization problem for $Q_t(\cdot)$ and $R_t(\cdot)$.

Algorithm. Our algorithm can be summarized in a few short steps:

1. Guess parameters $\theta^{(0)}$
2. Run the Kalman filter and smoother using $\theta^{(0)}$ to obtain $\{\widehat{\zeta}^{(0)}_{i,t|T}\}_{t=1}^{T}$ and $\{M^{(0)}_{i,t|T}\}_{t=1}^{T}$.
3. **E-step:** Write down the complete information likelihood (9). Integrate with respect to the unobservable distribution (which comes for "free" from the Kalman smoother). This yields $\mathcal{L}(\theta^{(0)})$ in terms of $\{\widehat{\zeta}^{(0)}_{i,t|T}\}_{t=1}^{T}$ and $\{M^{(0)}_{i,t|T}\}_{t=1}^{T}$.

[65] Recall that $\widehat{\zeta}_{i,t|T} = \begin{bmatrix} \widehat{z}_{i,t|T} & \widehat{z}_{i,t-1|T} \end{bmatrix}$.

[66] As we discussed in Section 2.1, we separate the income process parameters θ_0 from the parameters that govern the employment process. Section 1 and Appendix A of Braxton et al. (2025) have a detailed discussion on the statistical assumptions that are needed to separate the income process parameters and employment process parameters into two distinct groups.

4. **M-step:** Maximize $\mathcal{L}(\theta^{(0)})$ with respect to $\theta^{(0)}$. $\mathcal{L}(\theta^{(0)})$ is concave, so first order conditions are necessary and sufficient and yield simple updating formulas. This yields the new guess $\theta^{(0)} \to \theta^{(1)}$.

5. Run the Kalman filter and smoother again to obtain the new unobservable distribution $\{\widehat{\zeta}^{(1)}_{i,t|T}\}_{t=1}^{T}$ and $\{M^{(1)}_{i,t|T}\}_{t=1}^{T}$.

6. Repeat until $|\theta^{(N)} - \theta^{(N+1)}| < \epsilon$, where $\epsilon > 0$ is a prespecified tolerance.

A.3 Monte Carlo Evidence

In this appendix, we use a series of Monte Carlo exercises to establish identification and to show how simpler GMM style procedures fail to work in this setting because of the dynamic updating of an individual's lagged income rank.

Identification. We start by numerically establishing identification as in Altonji et al. (2013). For this exercise, we hypothesize a set of parameters and simulate a series of income histories. We then apply our estimation routine on this simulated data, and show that the parameters which maximize the likelihood are close to the hypothesized parameters used to simulate the data. The hypothesized parameters are the estimates obtained by applying our filter to our baseline income definition, AGI less interest and dividend income, on our baseline sample of Form 1040 income histories for individuals linked to the CPS-ASEC.[67] Simulating data for our income process also requires that we take a stance on the statistical process for unemployment. As in our quantitative model in Section 4, we assume that the unemployment probability is a cubic function of an agent's lagged earning rank when employed, but is a constant probability when unemployed.[68] We simulate $N = 25,000$ individuals for $T = 8$ periods, the number of periods between 25 and 60, inclusively. We simulate $D = 40$ Monte Carlo draws of this experiment, and Figure 13 presents the results.

In panel (a) of Figure 13 we present the estimates of the variance of the shocks to permanent income among the employed as a function of lagged income rank from the MC exercise. The black, solid line corresponds to the true estimate that is used to simulate data in the MC exercise. The blue dashed line is our mean estimate across the 40 MC simulations, and the red dashed lines correspond to a 95 percent simulation interval. The figure shows that the true

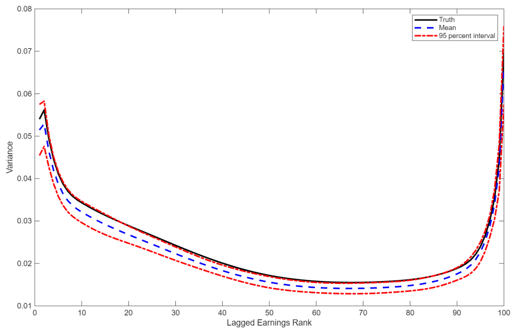
[67] Additionally, in the MC exercise, we do not consider time-variation and simulate data corresponding to the 1970s parameter estimates.

[68] In particular, we estimate equation (6) and the results are presented in Table 3.

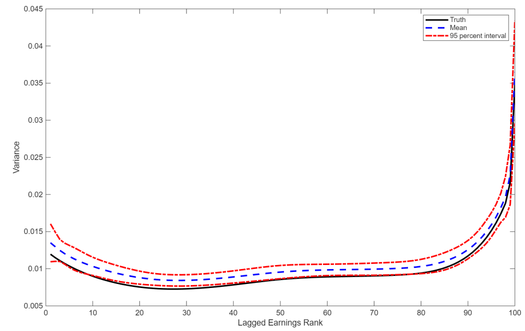
parameter values are within our simulation interval for nearly the entire distribution. The remaining panels of Figure 13 show that we obtain similar results for the variance of transitory shocks, the variance of permanent shocks to the non-employed (and non-filing) as well as the mean of permanent shocks and the mean of permanent shocks for the non-employed/non-filing. These results highlight that our estimation procedure is able to accurately recover the nature of income shocks across the income distribution.

Figure 13: Monte Carlo Results: Recovering Parameters by Lagged Income Rank

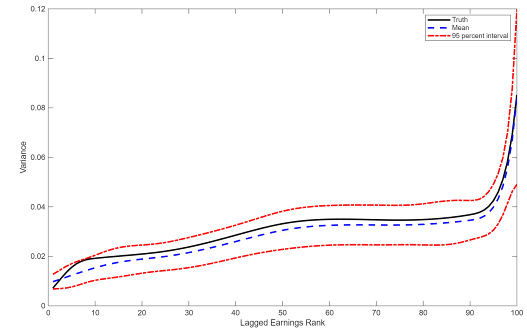
(a) Variance Permanent Shock



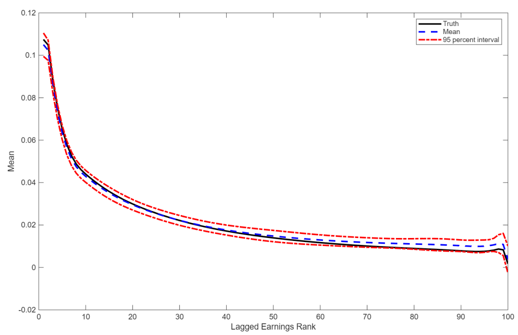
(b) Variance Transitory Shock



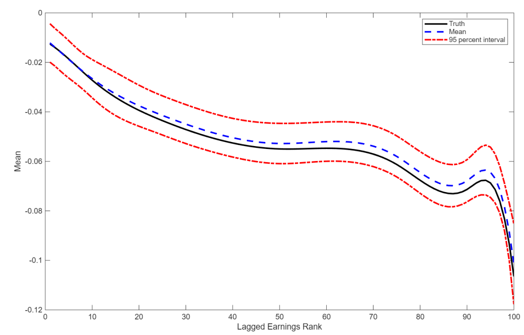
(c) Variance of Permanent Shock, Non-employed



(d) Mean Permanent Shock



(e) Mean Permanent Shock, Non-employed



Note: The figure presents the results of the Monte Carlo exercise in which we establish local identification of our model. In each panel, the black, solid line corresponds to our estimates from the 1970s for AGI less interest and dividend income, our assumed data generating process, while the blue dashed line represents the mean estimate across Monte Carlo draws from estimating our model's parameters on the simulated data. The red dash-dotted lines are the 95% simulation intervals of the point estimate across Monte Carlo draws. Panel (a) presents permanent income risk, panel (b) presents transitory income risk, panel (c) presents permanent income risk for individuals who are classified as non-employed / non-filers, panel (d) presents the mean of permanent shocks, and panel (e) presents the mean of permanent shocks for individuals who are classified as non-employed/non-filers.

GMM style estimation. We next examine how a GMM style estimation, which uses functions of means and variances for identification would perform in recovering the parameters of our income process. For intuition for how this type of GMM style procedure works, let us first consider a simpler model where the parameters do not vary by lagged income rank. Specifically, consider the following:[69]

$$\begin{aligned} y_{i,t} &= \begin{cases} z_{i,t} + \omega_{i,t} & \text{if } l_{i,t} = E \\ \cdot & \text{if } l_{i,t} = N \end{cases} \\ \omega_{i,t} &\sim N\left(0, R\right), \end{aligned} \tag{10}$$

where $\omega_{i,t}$ is independent of $z_{i,t}$ conditional on $l_{i,t}$ and $z_{i,t}$ evolves according to:

$$\begin{aligned} z_{i,t+1} &= z_{i,t} + B(l_{i,t+1}) + \nu_{i,t+1} \\ \nu_{i,t+1} &\sim N\left(0, Q(l_{i,t+1})\right) \\ z_{i,0} &\sim N(0, Q_0(y_0)). \end{aligned} \tag{11}$$

It is straightforward to verify that the parameters from the simple process in (10) and (11) are identified from simple moments using the following formulas:[70]

$$\begin{aligned} B(E) &= \mathbb{E}[y_{i,t+1} - y_{i,t} | l_{i,t} = l_{i,t+1} = E] \\ B(N) &= \mathbb{E}[y_{i,t+2} - y_{i,t} | l_{i,t} = l_{i,t+2} = E, l_{i,t+1} = N] - \mathbb{E}[y_{i,t+1} - y_{i,t} | l_{i,t} = l_{i,t+1} = E] \\ Q(E) &= \mathbb{V}[y_{i,t+2} - y_{i,t} | l_{i,t} = l_{i,t+1} = l_{i,t+2} = E] - \mathbb{V}[y_{i,t+1} - y_{i,t} | l_{i,t} = l_{i,t+1} = E] \\ Q(N) &= \mathbb{V}[y_{i,t+2} - y_{i,t} | l_{i,t} = l_{i,t+2} = E, l_{i,t+1} = N] - \mathbb{V}[y_{i,t+1} - y_{i,t} | l_{i,t} = l_{i,t+1} = E] \\ R &= (2\mathbb{V}[y_{i,t+1} - y_{i,t} | l_{i,t} = l_{i,t+1} = E] - \mathbb{V}[y_{i,t+2} - y_{i,t} | l_{i,t} = l_{i,t+1} = l_{i,t+2} = E]])/2 \end{aligned} \tag{12}$$

One could then condition these formulas on the date-t income rank to arrive at an estimate of the parameters of the income process as a function of an individual's lagged income. We will refer to this estimation procedure as the GMM estimation approach as well as the "simple" approach. Figure 14 presents the results of applying the "simple" approach on our simulated data from the MC exercise. In the figure, the green, solid line with circle markers, reports the mean estimate of the parameters across MC simulations while the red-dashed line reports a 95 percent simulation interval.

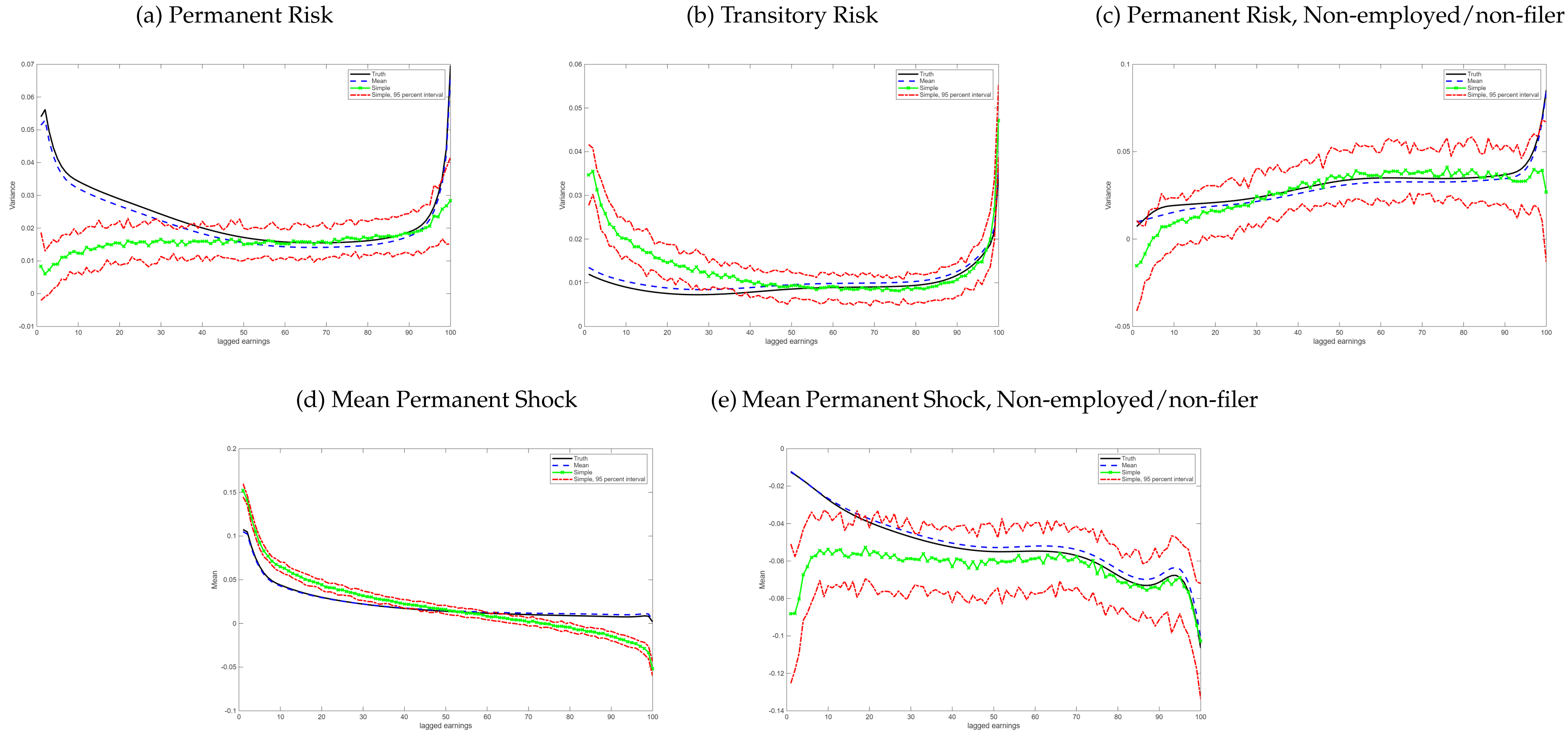
[69] This notation differs slightly from the main text, where labor-market status is written as the vector $l_{i,t} = [l_{E,i,t}\ l_{N,i,t}]'$, with $l_{E,i,t}$ and $l_{N,i,t}$ denoting indicators for employed and non-employed/non-filing status. Here, to simplify the derivation, we write $l_{i,t} \in \{E, N\}$ for the household's labor-market state.

[70] See Appendix B.1 of Braxton et al. (2025).

Panel (a) of Figure 14 shows that the “simple" approach is not able to recover the parameters of the income process for the bottom 30 percent of the distribution. While the data generating process (DGP) exhibits declining variance of permanent shocks as an individual moves from the lowest ranks towards the 30th percentile, the simple approach fails to capture this pattern and recovers a slightly increasing pattern. Additionally, the simple approach only records a modest uptick in the variance of shocks to permanent income in the far right tail, while the DGP exhibits a much sharper increase.

Additionally, Panel (b) of Figure 14 shows that the simple approach incorrectly infers a very high level of transitory risk for the lowest-income households and a sharply declining profile of transitory risk with income. Thus, panels (a) and (b) show that the simple approach struggles to distinguish permanent from transitory risk at the bottom of the distribution. By contrast, our estimation procedure accurately recovers the DGP in this region. The key difference is that our procedure dynamically updates an individual’s rank, whereas the GMM style approach conditions on the initial rank used in the simple moment formulas.

Figure 14: Monte Carlo Results: Recovering Parameters Using a GMM Approach



Note: The figure presents the results of the Monte Carlo exercise in which we examine the ability of a GMM style approach to estimate our income process. In each panel, the black, solid line corresponds to our estimates from the 1970s for AGI less interest and dividend income, our assumed data generating process, while the blue dashed line represents the mean estimate across Monte Carlo draws from estimating our model's parameters on the simulated data. The green-x line is the mean estimate of the simple model computed using equations (12) while the red dash-dotted lines are the 95% simulation intervals of the point estimate of the simple model across Monte Carlo draws. Panel (a) presents permanent income risk, panel (b) presents transitory income risk, panel (c) presents permanent income risk for individuals who are classified as non-employed / non-filers, panel (d) presents the mean of permanent shocks, and panel (e) presents the mean of permanent shocks for individuals who are classified as non-employed/non-filers.

B Time aggregation

In this appendix we discuss the role of time aggregation. Our data is only ever observed in 5-year intervals. We deal with time aggregation in two ways. First, we note that it is possible to translate an income process with a 1-year time step into a 5-year time step by exploiting the random walk nature of our income process. Second, we show how the output of our filter for the implied shock to permanent income is very similar across different frequency of observations.

Time aggregation: theory. For ease of exposition, we omit drift terms, assume that the permanent income innovations $\nu_{i,t}$ are iid, and ignore non-filers. Under the annual income process, permanent income evolves according to

$$z_{i,t} = z_{i,t-1} + \nu_{i,t}.$$

Iterating this process forward five years yields

$$z_{i,t} = z_{i,t-5} + \nu_{i,t} + \nu_{i,t-1} + \nu_{i,t-2} + \nu_{i,t-3} + \nu_{i,t-4}.$$

We are therefore estimating the following permanent income process on our data:

$$z_{i,t} = z_{i,t-5} + \widehat{\nu}_{i,t}, \qquad \widehat{\nu}_{i,t} = \nu_{i,t} + \nu_{i,t-1} + \nu_{i,t-2} + \nu_{i,t-3} + \nu_{i,t-4}.$$

If the annual innovations are independent and have a common variance Q, then

$$\mathrm{Var}\left(\widehat{\nu}_{i,t}\right) = 5Q.$$

Thus, we obtain the annualized variance of permanent income innovations by dividing the estimated five-year variance by the length of the interval, which is five in our setting.

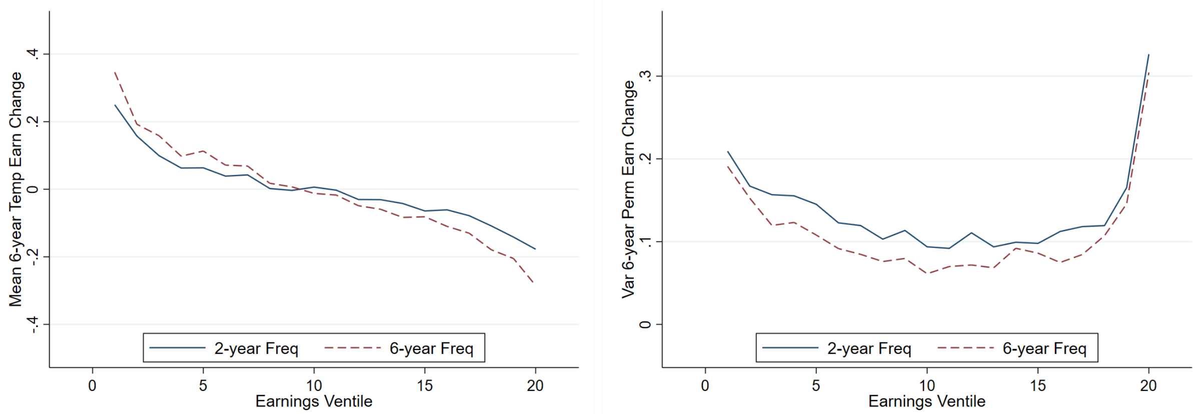
Time aggregation in practice. In this appendix, we use the PSID sample to examine how the frequency of observations impacts our estimation of the risk that individuals face.[71] In particular, to evaluate the impact of filtering at a 5-year horizon, we estimate our income process on the PSID for two horizons: 2-years and 6-years. We then compare the implied mean and variance of 6-year changes in permanent earnings (using our individual level estimates of permanent income) conditional on ventiles of recent earnings. We plot the conditional mean and variance of these changes in Figure 15 below.

[71] See Appendix C.5 for more details on how we estimate our income process on a PSID sample.

Figure 15: Permanent Income Shocks by Frequency of Observation

(a) Mean of Permanent Shocks

(b) Variance of Permanent Shocks



Note: The figure presents results for estimating our income process on the PSID where we observe the data every 2-years (blue, solid line) and every 6-years (red, dashed line). Panel (a) shows the mean of the shock to permanent earnings, and panel (b) shows the variance of shocks to permanent earnings

As Figure 15 verifies above, the conditional means (panel (a)) and variances (panel (b)) between filtering frequency are qualitatively very similar. Aside from a modest vertical shift, the shape of the variance profile is almost identical when filtered at different frequencies.[72]

C Additional Empirical Results

In this appendix, we present a series of additional empirical results.

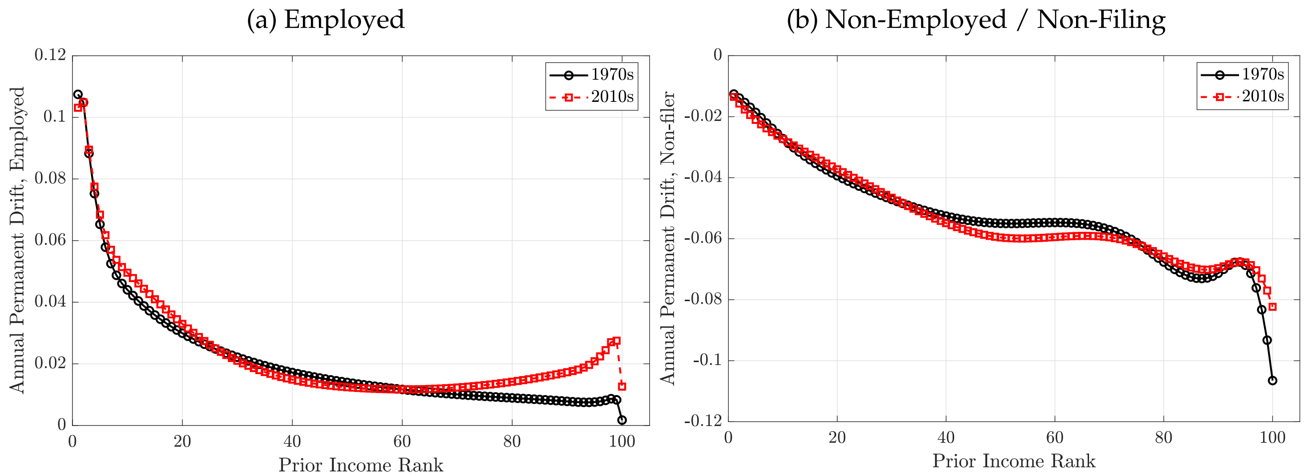
C.1 Additional model estimates

In this section, we report additional estimates from the baseline model introduced in Section 3.1

Mean shocks to permanent income. In Figure 16 we present the mean shock to permanent income as a function of lagged income rank for employed individuals (Panel (a)) as well as non-employed/non-filers (Panel (b)). Among employed individuals, we observe substantial mean reversion: households at low lagged income ranks experience large positive mean shocks to permanent income, while higher-ranked households exhibit much smaller mean shocks. We

[72]Note the difference in the levels of variances reported in Figure 15 and 26 is because of the use of ventiles in Figure 15.

Figure 16: Mean of Shocks to Permanent Income



Note: Figure presents the results of estimating the income process in Section 2.1. Panel (a) plots the full profile of mean shocks to permanent income among the employed as a function of lagged income rank for the 1970s and 2010s. Panel (b) plots the full profile of mean shocks to permanent income among the non-employed/non-filing as a function of lagged income rank for the 1970s and 2010s. In both figures we present an annualized mean and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

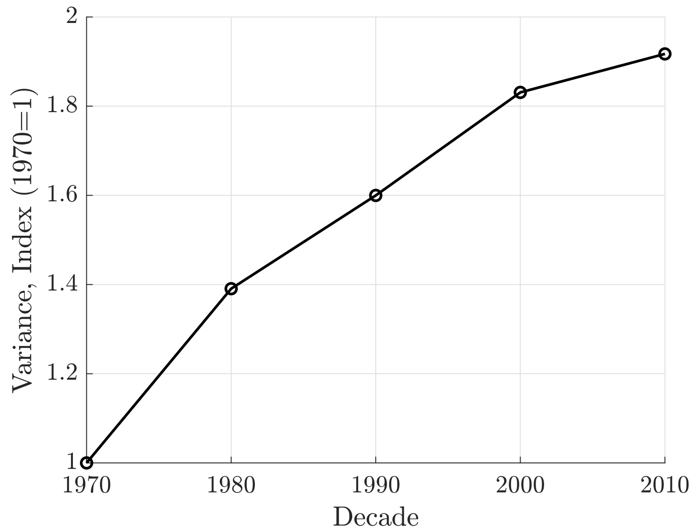
additionally find some evidence of an increase in the mean shock to permanent income for households between the 80th and 99th percentiles from the 1970s to the 2010s. Among non-employed/non-filers, we find that the magnitude of permanent income declines increases with lagged income rank, implying that higher-income households experience larger permanent income losses during periods of non-employment or non-filing. We do not see much of a change in this pattern between the 1970s and the 2010s.

Initial draw of permanent income. Our method also produces an estimate of the initial dispersion in permanent income. In Figure 17, we plot the variance of the initial draw of permanent income by decade. The figure shows that there has been a steady increase in initial permanent income inequality over time.

C.1.1 Additional results: estimates by self-employment status

In this appendix, we present additional results from our estimation which splits the sample into the non-self employed and the self-employed. Figure 18 presents the profiles of transitory income risk for the employed and permanent income risk among the non-employed/non-filers, separately for the self-employed and non-self-employed. These additional components of in-

Figure 17: Variance of initial draw of permanent income over time



Note: Figure presents the results of estimating the income process in Section 2.1, and shows the variance of the initial draw of permanent income by decade. The y-axis is set such that the variance in 1970 is equal to one. Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

come risk display broadly similar patterns across self-employment status. For transitory risk, both groups exhibit relatively flat profiles through most of the prior income distribution, followed by a sharp increase at the very top in the 2010s. The levels and changes are broadly similar for the self-employed and non-self-employed. For permanent risk among the non-employed/non-filers, both groups also exhibit higher risk in the 2010s at the top of the income distribution.

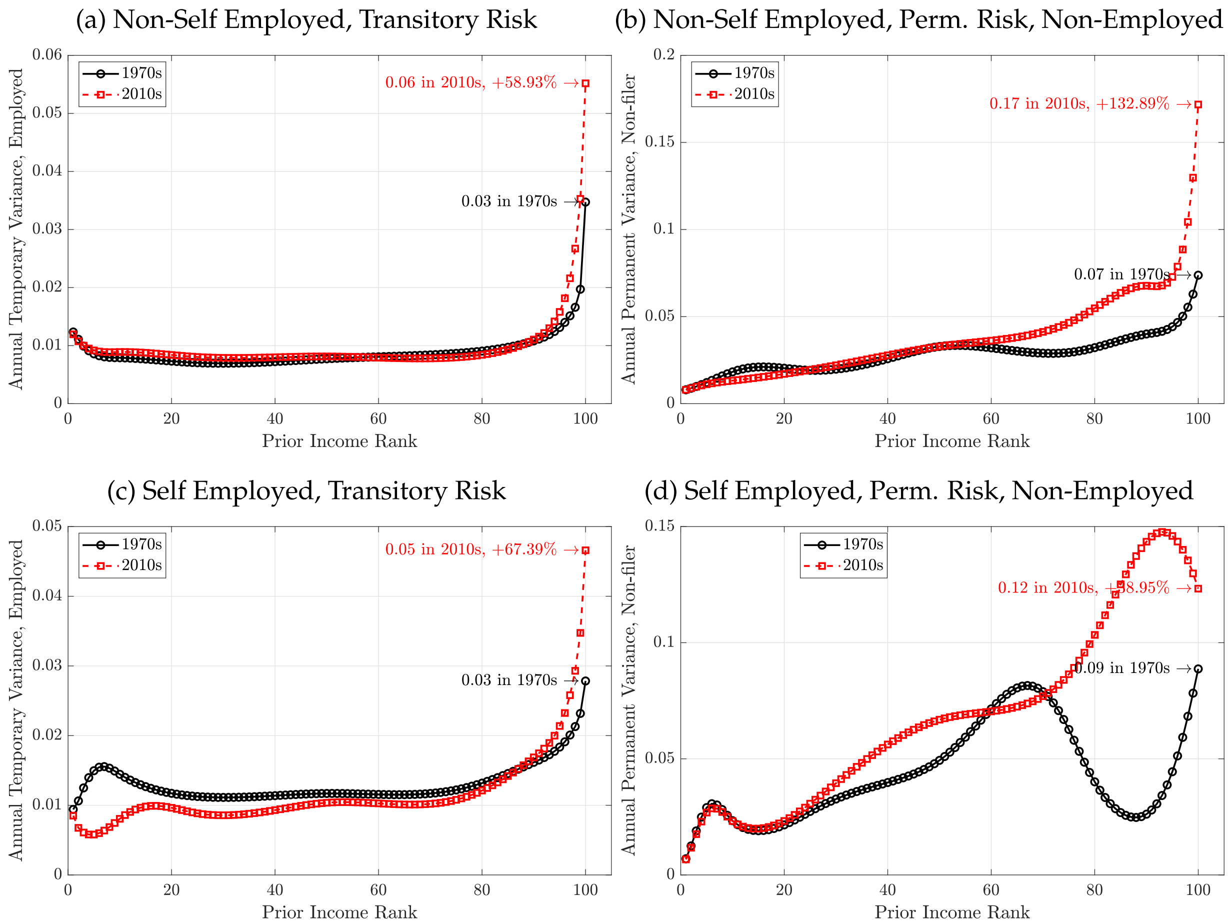
C.2 Alternative income definitions

In this appendix, we show that our results are robust to a series of alternative income definitions.

C.2.1 Adjusted Gross Income (AGI)

We first show that our results are robust to using adjusted gross income (AGI) as our measure of income in Figure 19. Panel (a) shows the evolution of permanent income risk among the employed using AGI for each decade from 1970 to 2010 for selected percentiles of the income distribution. The figure shows that households in the 95th and 90th percentiles of the income distribution have experienced the largest increases in income risk relative to households lower in the income distribution. Panel (b) shows that at the very top of the income distribution,

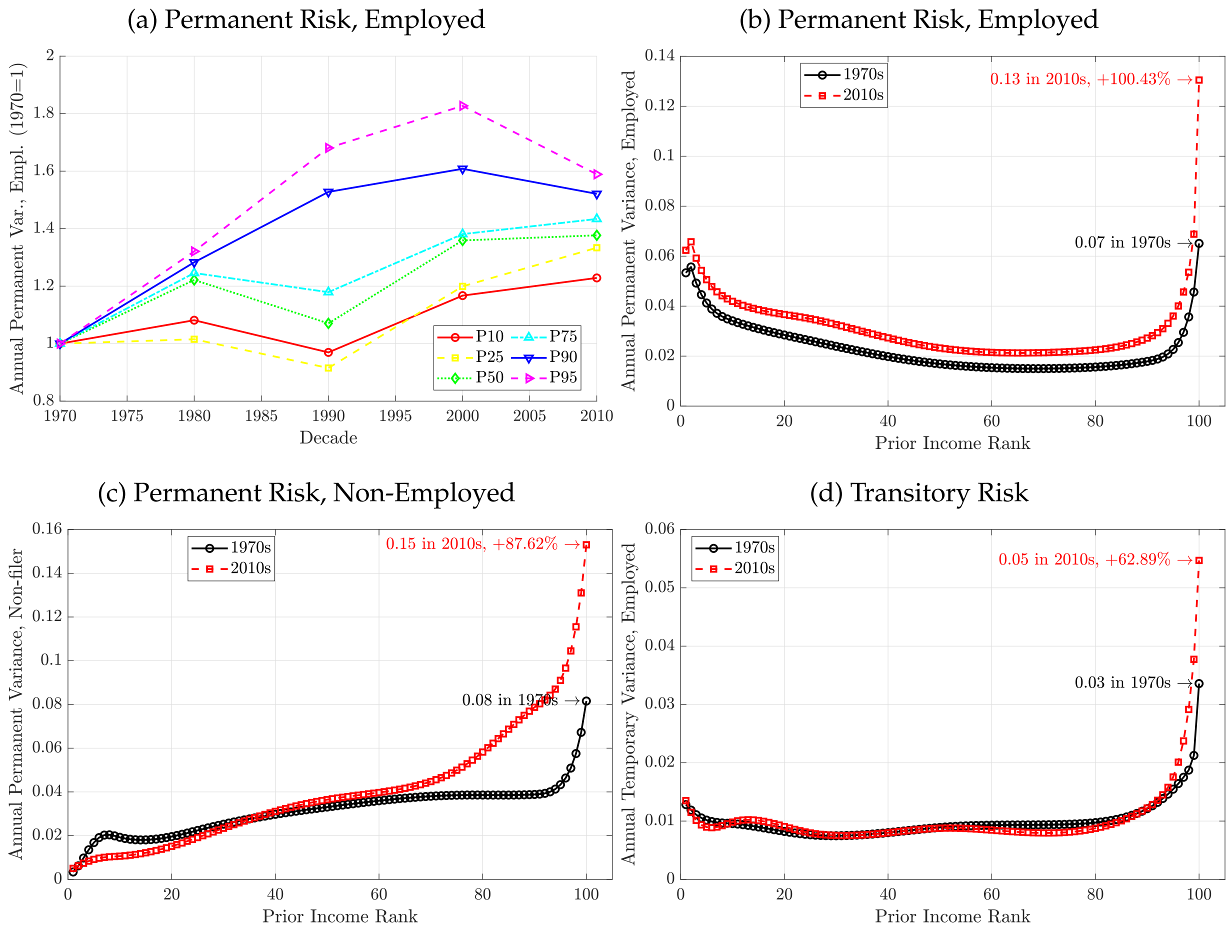
Figure 18: Additional Parameter Estimates by Self-Employment Status



Note: Figure presents additional results from estimating the income process in Section 2.1 separately by self-employment status. Panels (a) and (b) report estimates for individuals classified as non-self-employed, while Panels (c) and (d) report estimates for individuals classified as self-employed. Panels (a) and (c) plot the full profile of transitory income risk among the employed as a function of lagged income rank for the 1970s and 2010s. Panels (b) and (d) plot the full profile of permanent income risk among the non-employed/non-filing as a function of lagged income rank for the 1970s and 2010s. In all panels, we report annualized variances. Individuals are ranked by lagged income in the full sample, so that a given rank corresponds to the same position in the overall income distribution for the self-employed and non-self-employed. The 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

permanent income risk has effectively doubled since the 1970s. Finally, panels (c) and (d) show that permanent income risk among the non-employed, as well as transitory income risk, have increased for high-income households since the 1970s.

Figure 19: Evolution of Income Risk Using Adjusted Gross Income (AGI)



Note: Figure presents the results of estimating the income process in Section 2.1 where our measure of income is adjusted gross income (AGI). Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income, while panel (c) plots the full profile of shocks to permanent income among the non-employed. Panel (d) plots the full profile of shocks to transitory income. In panels(b)-(d) figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Note in panels (b)-(d) we annualized variances.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

C.2.2 Wage and Salary Income (WSI)

Next, we examine the evolution of income risk across the income distribution and over time using wage and salary income (WSI) as our measure of income. Figure 20 presents the results of estimating the income process described in Section 2.1 with income measured using WSI. Panel (a) shows the evolution of permanent income risk across the income distribution since the

1970s for selected percentiles. The figure shows that high-income households have experienced the largest increase in permanent income risk while employed. Panel (b) shows that permanent income risk has increased across the income distribution between the 1970s and the 2010s, with the largest increase occurring among high earners. In particular, for individuals at the very top of the income distribution, permanent income risk has increased by nearly 60%. Panel (c) shows that permanent income risk has increased during spells of non-employment for high earners and has effectively doubled at the very top of the income distribution. Panel (d) plots the profile of transitory income risk in the 1970s and the 2010s and shows that, when income is measured using WSI, transitory risk is very similar across the two time periods except in the right tail of the distribution. Taken together, these results show that when income is measured using WSI, both permanent and transitory income risk have increased for top earners.

C.2.3 Removing Capital Gains

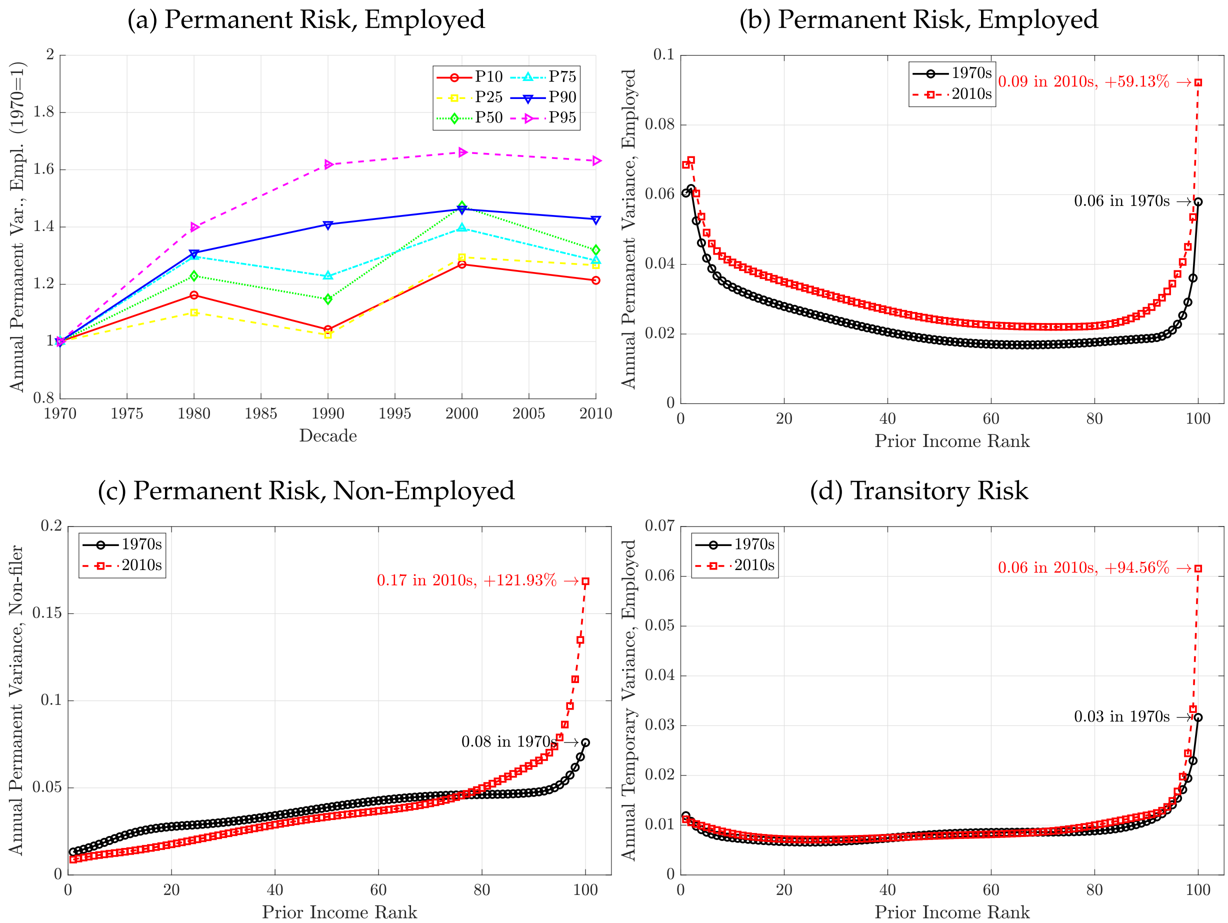
In this appendix, we examine whether our estimates of income risk are sensitive to the inclusion of capital gains in our income measure. Because capital gains can only be separately identified in our data beginning in 1994, we restrict the estimation sample to 1994 onward for this exercise. We then re-estimate our income process allowing the variance of income shocks to vary by lagged income rank and age, but not by decade.

Figure 21 compares estimates obtained using our baseline income measure (black solid line with circle markers) to estimates obtained when capital gains are removed from income (red dashed line with square markers). Panels (a) and (b) show that the estimated profile of permanent income risk by lagged income rank is nearly identical whether or not capital gains are included in the income measure. Even at the very top of the income distribution, excluding capital gains has little effect on the estimated variance of permanent shocks. Panels (c) and (d) present the corresponding estimates for transitory risk. The overall shape of the transitory risk profile is again very similar across specifications. However, transitory risk at the very top of the income distribution is modestly lower when capital gains are excluded. This pattern is consistent with capital gains primarily contributing additional transitory volatility among top income households rather than affecting estimates of permanent income risk.

C.3 Random sample of 1040s

In this appendix, we examine the evolution of income risk across the income distribution and over time using a 2% random sample of individuals from the 1040s data and our baseline mea-

Figure 20: Evolution of Income Risk Using Wage and Salary Income (WSI)

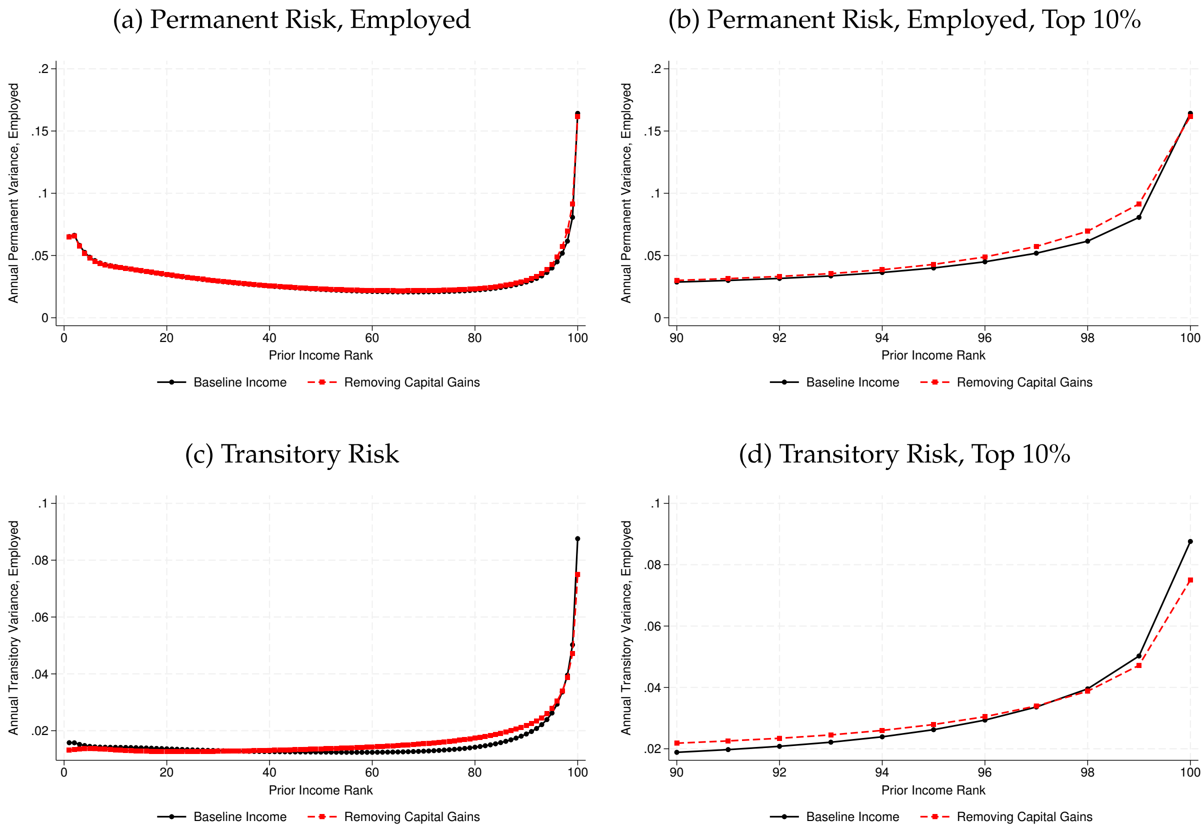


Note: Figure presents the results of estimating the income process in Section 2.1 where our measure of income is wage and salary income (WSI). Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income, while panel (c) plots the full profile of shocks to permanent income among the non-employed. Panel (d) plots the full profile of shocks to transitory income. In panels(b)-(d) figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Note in panels (b)-(d) we present an annualized variance.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

sure of income.[73] Figure 22 presents the results of estimating the income process described in Section 2.1 on this 2% random sample. Panel (a) plots the evolution of permanent income risk among the employed for selected percentiles of the lagged income distribution. The figure

[73]For this exercise, we randomly sample individuals. In our data, we observe the scrambled Social Security number (PIK) of a spouse when present. In cases where both members of a two-adult household are drawn into the sample, we assign each individual a weight of 1/2 in the estimation.

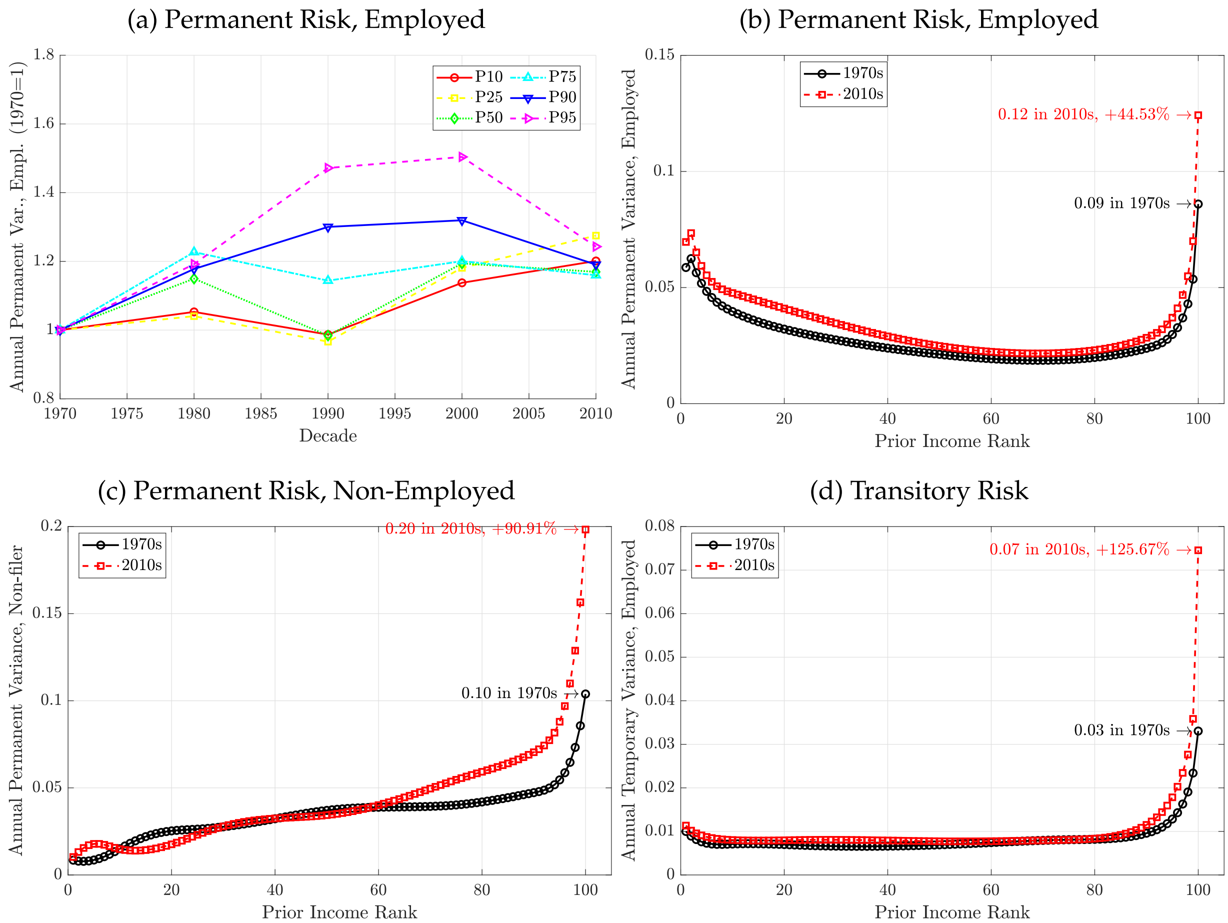
Figure 21: Evolution of Income Risk Removing Capital Gains



Note: Figure compares estimates of the income process described in Section 2.1 using two income measures: baseline income (black solid line with circle markers) and baseline income excluding capital gains (red dashed line with square markers). Because capital gains can only be separately identified beginning in 1994, the estimation sample for this exercise is restricted to 1994 onward. In this specification, the variance of income shocks is allowed to vary flexibly with age and lagged income rank but is restricted to be constant across decades. Panels (a) and (b) plot the estimated variance of permanent income shocks among employed individuals as a function of lagged income rank. Panels (c) and (d) plot the corresponding estimates for transitory income shocks. Panels (b) and (d) zoom in on the top 10 percent of the lagged income distribution. All variances are reported at an annual frequency.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

shows that permanent income risk has increased across the income distribution between the 1970s and the 2010s, with the largest increases occurring among individuals in the upper tail of the income distribution. Panel (b) shows the full profile of permanent income risk among the employed by lagged income rank in the 1970s and the 2010s. The figure shows that the increase in permanent income risk is pronounced among high-income individuals. Panel (c) shows that permanent income risk among the non-employed has increased for individuals above roughly the 60th percentile of the income distribution, with especially large increases at the top of the

Figure 22: Permanent and Transitory Risk Using Random Sample of 1040s



Note: Figure presents the results of estimating the income process in Section 2.1 using our baseline measure of income on a 2% random sample of 1040s. Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income, while panel (c) plots the full profile of shocks to permanent income among the non-employed. Panel (d) plots the full profile of shocks to transitory income. In panels(b)-(d) figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Note in panels (b)-(d) we present an annualized variance.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

income distribution. Finally, panel (d) shows that transitory income risk is very similar between the 1970s and the 2010s for most of the income distribution, but increases noticeably in the right tail, particularly above the 95th percentile. Taken together, these results show that our baseline findings are robust when estimating the income process using a random sample of 1040s.

C.4 Additional Results: Composition.

In this appendix, we summarize a set of additional results to highlight that our results are robust to different methods of controlling for changes in composition of workers within a household (Appendix C.4.1), occupation (Appendix C.4.2) and age (Appendix C.4.3).

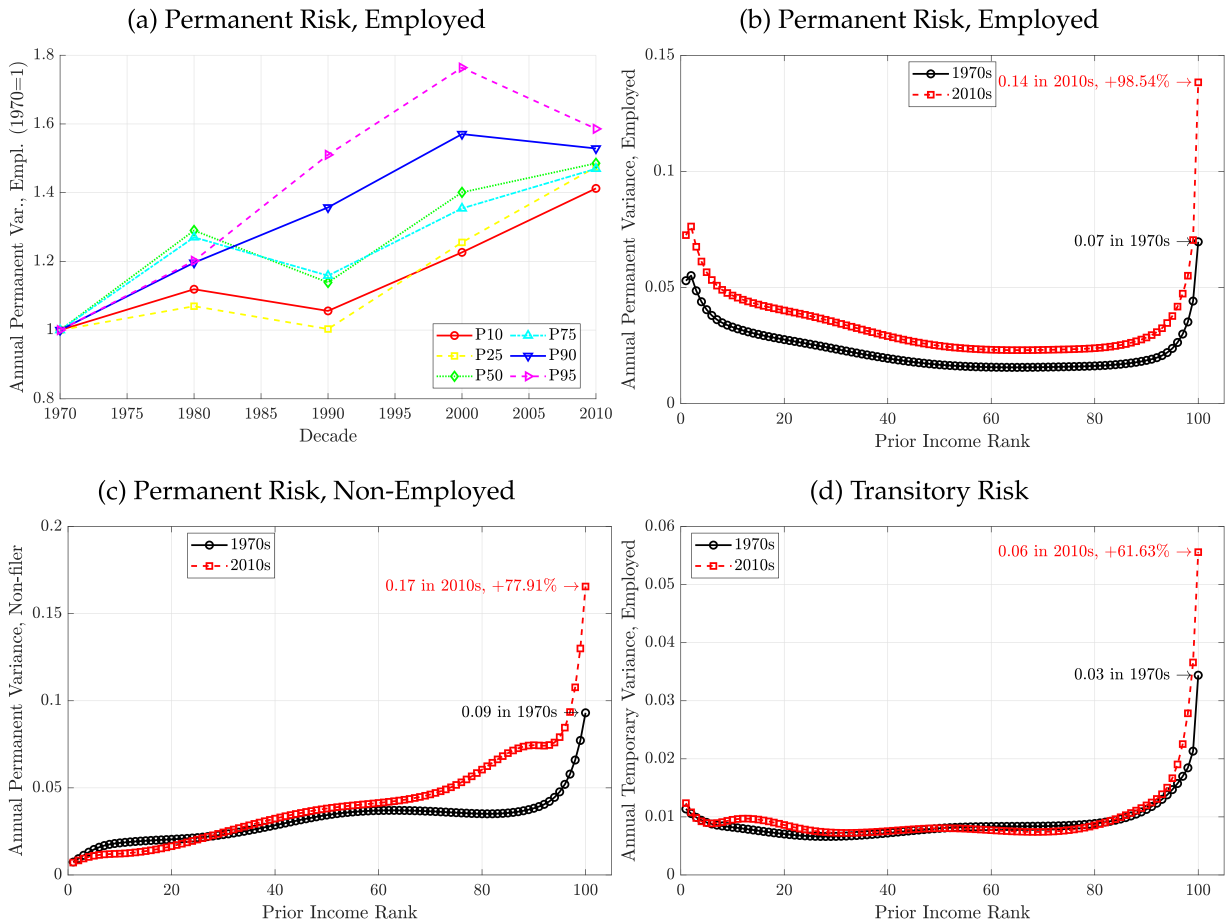
C.4.1 Alternative Residualization.

In this appendix, we show that our results are robust to altering our process for residualizing earnings to including fixed effects for the interactions between the number of adults filing and year. This specification allows the relationship between income and household filing status to vary flexibly over time and therefore helps control for changes in the gender and household composition of the labor market. Figure 23 presents the results. Panel (a) plots the evolution of permanent income risk among the employed by decade for selected percentiles of the lagged income distribution. Similar to our baseline results, permanent income risk increases over time across the distribution, with the largest increases occurring for individuals in the upper tail. Panel (b) shows the full profile of shocks to permanent income while employed for the 1970s and 2010s, and shows that the increase in permanent income risk is especially large at the very top of the income distribution. Panel (c) shows that permanent income risk among the non-employed also increases substantially for individuals in the upper half of the income distribution. Finally, panel (d) plots the profile of transitory income risk in the 1970s and the 2010s. As in our baseline results, transitory income risk is similar across the two time periods for most of the income distribution but increases among households at the top of the income distribution.

C.4.2 Ranking Income Within Occupation.

In this appendix, we show that our results are robust to ranking workers within their two-digit occupation. We use an individual's first reported occupation in the CPS-ASEC to classify an individual into an occupation, where we classify occupations using the classification system from Autor and Dorn (2013). We then rank individuals based on their residual log income within their two-digit occupation as well as by age and year. Figure 24 presents the results. Panel (a) plots the evolution of permanent income risk among the employed by decade for selected percentiles of the occupation-specific lagged income distribution. Similar to our baseline results, permanent income risk increases over time across the distribution, with the largest increases occurring for individuals in the upper tail. Panel (b) plots the full profile of permanent income risk among the employed as a function of lagged income rank within occupation in the

Figure 23: Evolution of Income Risk, Alternative Residualization



Note: Figure presents the results of estimating the income process in Section 2.1 using our baseline measure of income, where our process for residualizing income includes a set of fixed effects interacting year with number of adults filing. Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income, while panel (c) plots the full profile of shocks to permanent income among the non-employed. Panel (d) plots the full profile of shocks to transitory income. In panels(b)-(d) figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Note in panels (b)-(d) we present an annualized variance.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

1970s and the 2010s. The figure shows that permanent income risk increases across most of the distribution, but the increase is particularly pronounced among individuals at the very top of the distribution, where permanent income risk rises by nearly 100 percent. Panel (c) shows that permanent income risk among the non-employed also increases substantially for individuals in the upper half of the income distribution when ranking is performed within occupation. Finally, panel (d) plots the profile of transitory income risk in the 1970s and the 2010s. Consistent with our baseline results, transitory income risk is similar across the two time periods for most of the income distribution but increases in the right tail. Taken together, these results show that the increase in income risk for high-income individuals is not driven by differences across occupations but instead reflects changes within occupations.

C.4.3 Profiles by Age.

Finally, in this appendix we examine whether there is heterogeneity in the evolution of permanent income risk across the income distribution and over time by the *age* of the individual. To do so, we adjust the income process presented in Section 2.1 so that the basis functions that are allowed to vary by decade and lagged income rank are also allowed to vary by whether the individual is younger than age 40 or age 40 and older. In this estimation, we remove the inclusion of an age quadratic from the specification. We present the resulting variance of permanent income for the employed in Figure 25.[74]

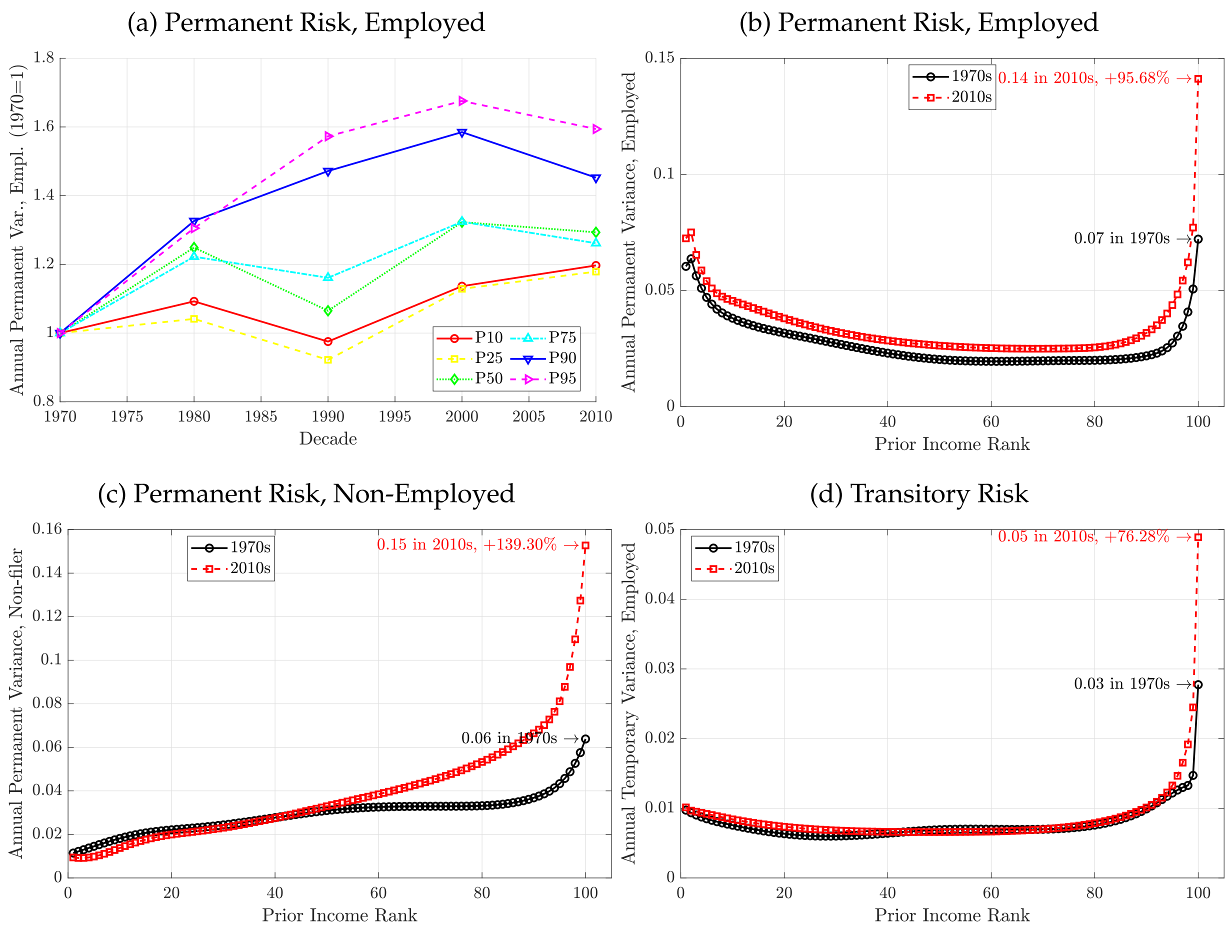
The left panel of Figure 25 shows the profile of permanent income risk for individuals under the age of 40 for the 1970s (black, solid line with circle markers) and the 2010s (red, dashed line with square markers) by lagged income rank. The figure shows that the U-shaped nature of permanent income risk is present among younger individuals, and that among the young the largest increases in risk occur for higher earners. At the top of the distribution, permanent income risk has increased by approximately 93%. Panel (b) shows the results for permanent income risk among individuals age 40 and older. We obtain similar results for older individuals, both in terms of the U-shaped relationship between risk and income rank and in terms of the increase in risk being concentrated at the top of the income distribution. In particular, for individuals at the top of the income distribution permanent income risk has increased by 90%. We do, however, find that the level of income risk for high-income individuals is higher among older individuals. Taken together, these results indicate that the increase in permanent income risk among high-income individuals has occurred for both younger and older individuals.

C.5 PSID Estimation and Results

In this appendix, we estimate our income process using publicly available data from the PSID. We recover the same U-shaped profile of permanent income risk across the income distribution as in our administrative data. In particular, permanent income risk rises sharply toward the

[74] The results for the other parameters of the income process are available upon request.

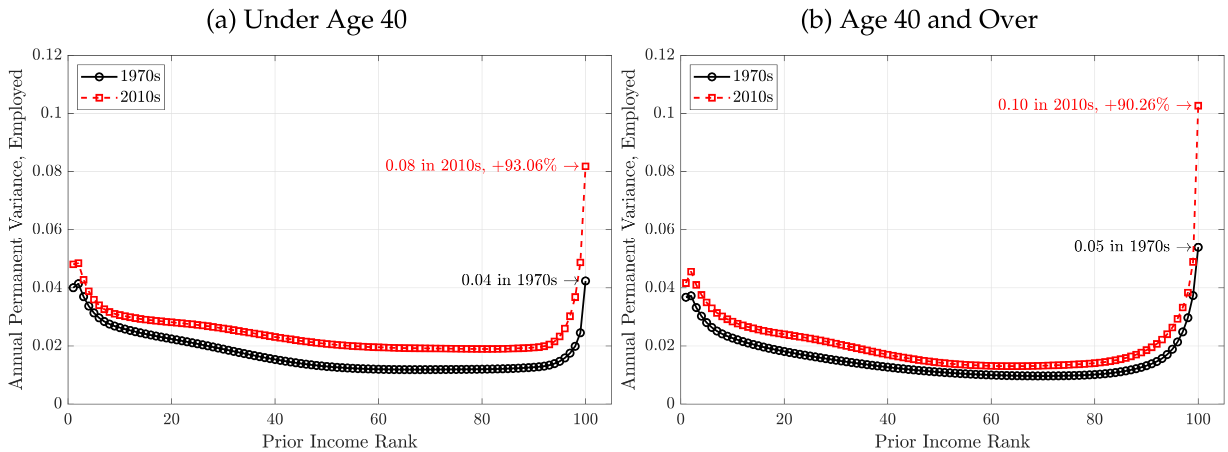
Figure 24: Evolution of Income Risk, Ranking Within 2-Digit Occupation



Note: Figure presents the results of estimating the income process in Section 2.1 using our baseline measure of income and ranking individuals within their 2-digit occupation. Panel (a) plots the time series of the variance of shocks to permanent income (y-axis) among the employed by decade from the 1970s to the 2010s (x-axis) for selected percentiles of the lagged income distribution. In this figure, we have normalized the values on the y-axis to be equal to 1 in 1970s. Panel (b) plots the full profile of shocks to permanent income among the employed as a function of lagged income, while panel (c) plots the full profile of shocks to permanent income among the non-employed. Panel (d) plots the full profile of shocks to transitory income. In panels(b)-(d) figures we present an annualized variance and the 1970s correspond to the black, solid line with circle markers, while the 2010s correspond to the red, dashed line with square markers. Note in panels (b)-(d) we present an annualized variance.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

top of the distribution. Thus, the convex permanent income risk that is central to our analysis is also present in the PSID and is not a feature specific to our administrative tax data.

Figure 25: Permanent Income Risk Among Employed by Income Rank and Age



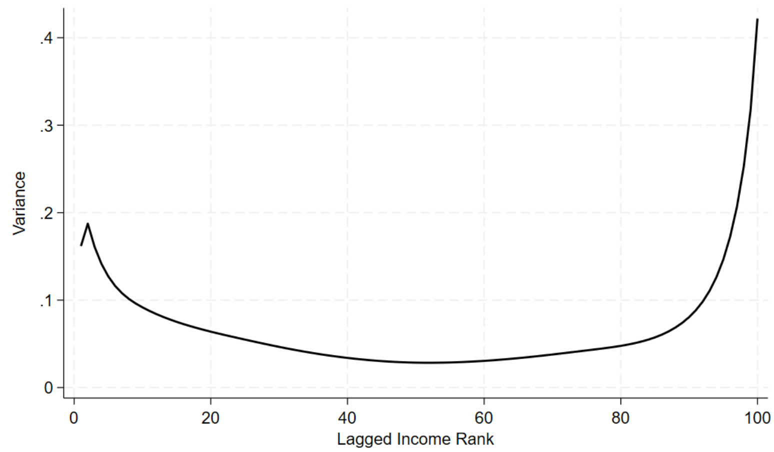
Note: Figure presents the results of estimating the income process in Section 2.1 using our baseline measure of income, where the profile of shocks as a function of lagged income rank is allowed to vary by age (under 40, or 40 and over) as well as decade. Panel (a) plots the full profile of shocks to permanent income among the employed as a function of lagged income for individuals under the age of 40, while panel (b) plots the full profile of shocks to permanent income among the employed for individuals over the age of 40. Note in both panels we present an annualized variance.
Source: 1973, 1979, 1981-1991, 1994, and 1996-2020 Current Population Survey Annual Social and Economic Supplement linked to 1040s in the years 1969, 1974, 1979, 1984, 1989, 1994, 1999, 2004, 2009, 2014, 2019.

PSID Sample. We use data from the PSID for the years 1971 to 2013.[75] To mimic the 5-year observation structure of our tax data, we impose that we observe income every 6-years in our PSID dataset.[76] To maintain comparability with our baseline results, we impose similar sampling criteria on the PSID where possible. In particular, for our PSID sample we require: (1) individuals to be between the ages of 25 and 60 (inclusive), and (2) to have income over the minimum cutoff twice and in 50% of years between when they first and last satisfy the cutoff. We additionally drop the SEO oversample in our estimation.

PSID Results. In Figure 26, we present the variance of shocks to permanent earnings as a function of lagged earnings ranks. The figure shows that in the PSID, we obtain a similar pattern of permanent income risk being U-shaped. Additionally, we also find that permanent income risk increases sharply as we move through the upper tail. Thus, we conclude that the PSID also features convex permanent income risk.

[75] We use the PSID earnings histories that are made available from the CNEF for the years 1971 to 2013. We thank them for making this data available to us.
[76] We use a 6-year interval in this exercise because the PSID became a bi-annual survey start in the 1990s, which precludes us from using a 5-year interval over the entire sample period.

Figure 26: Permanent income risk in the PSID



Note: Figure plots the estimated variance of shocks to permanent income as a function of lagged income rank using PSID data from 1971 to 2013.

D Capitalizing interest and dividend income

In this appendix, we discuss how we capitalize interest and dividend income to arrive at a measure of wealth. We follow Smith, Zidar, and Zwick (2023) and impute household-level wealth from components of income, observable in 1040 tax forms, that originate from returns on components of wealth. Specifically, we capitalize taxable interest income and dividend income from the 1040 forms into imputed fixed-income and C-corp wealth. The strategy can be described as follows.

Let $w^c_{i,t}$ be household i's wealth in component c at date t. In the 1040 form, household i reports the income generated from this wealth component, $I^c_{i,t} = r^c_{i,t} w^c_{i,t}$, where $r^c_{i,t}$ is the net return of household i's wealth in component c at date t, which may vary across households due to differing portfolios within component c. If the net return $r^c_{i,t}$ for a household is known, then the household's wealth can be inferred as simply $w^c_{i,t} = \kappa^c_{i,t} I^c_{i,t}$ where $\kappa^c_{i,t} = \frac{1}{r^c_{i,t}}$ is the capitalization factor for household i's wealth in component c at date t.

Smith, Zidar, and Zwick (2023) compute capitalization factors for taxable interest income and dividend income by constructing portfolios and computing net returns on fixed-income and C-corp wealth, respectively. For imputing C-corp wealth, we do not observe capital gains so we use their capitalization factor restricted to load solely on dividend income.[77] This is homogeneous across individuals but varies over time. To capitalize fixed income wealth, we begin with their 3-tier classical minimum distance (CMD) specification, which is heteregenous across

[77] We thank Eric Zwick for sending us this capitalization factor.

individuals as sorted by interest income. We avoid sharp discontinuities and nonmonotinicities in imputed wealth implied by taxable interesst income at the cutoffs defining the 3 tiers by interpolating. Specifically, we assign the lowest-tier capitalization factor to the households below the 90th percentile of taxable fixed income wealth. We assign the 99th percentile to have the second-tier capitalization factor, and linearly interpolate between the first- and second-tier capitalization factor for households with fixed interest income percentiles between 90-99. We then assign the highest-tier capitalization factor to the 99.9th percentile, and linearly interpolate between the second-tier and highest-tier capitalization factors between the 99-99.9th percentile. We finally assign the highest-tier capitalization factor to those above the 99.9th percentile.

The result of this procedure is capitalized fixed-income and C-corp wealth for individuals in our sample, the sum of which we take to be our measure of household wealth. This can be best thought of as being the liquid components of income-generating wealth - we do not observe housing or pension wealth. Our wealth measure begins in 1974, when the taxable interest income and dividend income 1040 boxes begin to be observed in our data, and end in 2014 due to our capitalization factor series ending in 2016.

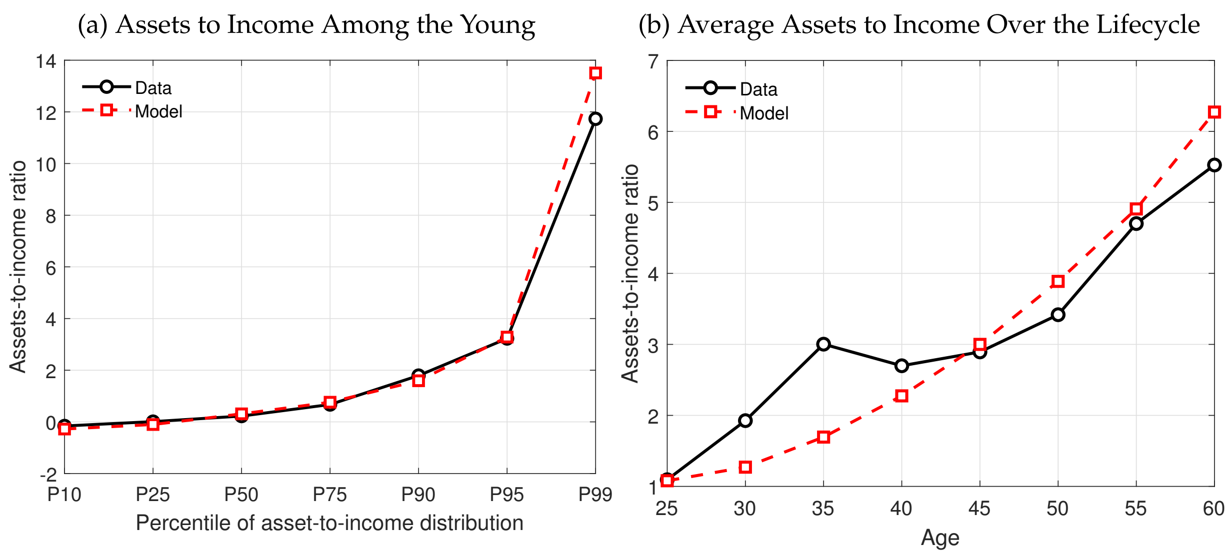
E Additional Results: Quantitative Model

In this appendix, we present a series of additional results from the quantitative model. In Appendix E.1 we present additional moments from our baseline estimation of the model. In Appendix E.2, we compare the model's savings response to changes in permanent and transitory income risk across the life-cycle to our empirical estimates. In Appendix E.3, we present the profiles of income risk used in the counterfactual where convex income risk is removed. Finally, in Section E.4, we show additional results from the quantitative experiment where we change in the income process over time.

E.1 Baseline Calibration

In this appendix, we present a series of additional moments from the baseline estimation of the model. In panel (a) of Figure 27, we plot the distribution of assets to income among young households (age 25) in the model (red dashed line with square markers) and the data (black solid line with circle markers). While the model is calibrated to match only the share of agents with zero wealth and the 95th percentile of assets to income, the figure shows that it captures the distribution of assets to income among young households very well across the distribution. In panel (b) of Figure 27, we plot the evolution of average assets to income over the life-cycle.

Figure 27: Additional Quantitative Model Estimates



Note: Panel (a) shows moments from the distribution of assets to income among age 25-year olds in the quantitative model. Panel (b) shows the ratio of assets to income across the working life-cycle in the quantitative model. In both figures, the red, dashed line with square markers, corresponds to the estimates from the quantitative model. The black solid line, with circle markers, corresponds to the estimates from the 1970s SCF+.

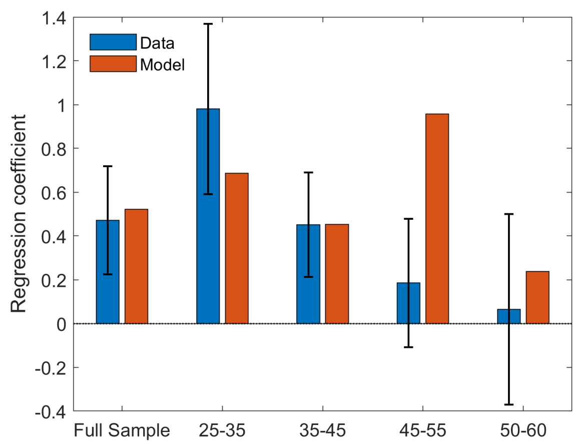
The model is calibrated to match the assets-to-income ratio at ages 25, 45, and 55, and the figure shows that it generates reasonable assets-to-income ratios at the other life-cycle stages.

E.2 Additional Results: Savings Response by Age

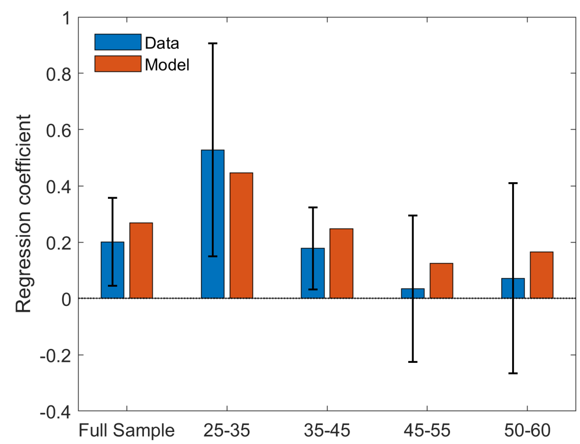
In this appendix, we examine the response to permanent and transitory income risk on savings by age. Panel (a) of Figure 28 reports the savings response to permanent income risk by age group, while panel (b) reports the corresponding response to transitory income risk. In both the data and the model, savings responses are largest for younger households and generally decline with age. For permanent income risk, the model reproduces the high savings response among households ages 25-35 and the lower responses among older households. For transitory income risk, the model similarly captures the declining age profile, with the largest responses early in the life cycle and smaller responses closer to retirement. Overall, the figure shows that the model is able to generate the main life-cycle pattern in the savings response to both permanent and transitory income risk.

Figure 28: Savings Response to Permanent & Transitory Income Risk By Age: Model and Data

(a) Permanent Risk



(b) Transitory Risk

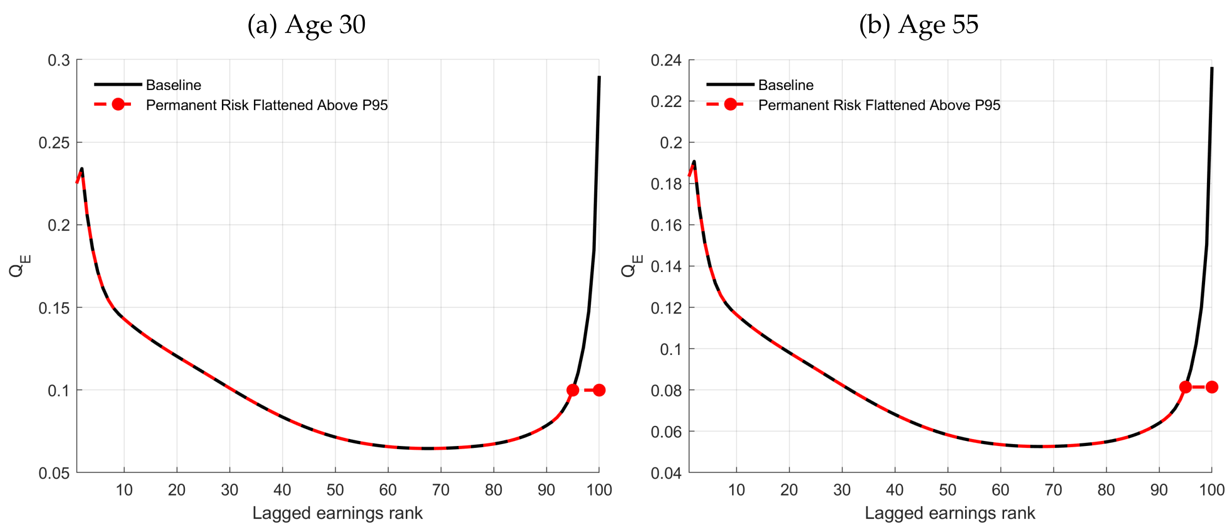


Note: The figure shows the savings response to permanent (panel (a)) and transitory (panel (b)) income risk in the quantitative model and in the data. Model based estimates are given by the orange bars, while the data estimates are represented by the blue bars. The full-sample estimates use all agents; the remaining estimates are estimated separately by age subsample. Error bars denote 99% confidence intervals for the data estimates.

E.3 Additional Results: Convex Income Risk Profiles

In this appendix, we present the income risk profiles used in the counterfactual exercise in Section 4.3 to examine the implications of convex permanent income risk. Figure 29 plots the baseline profile of permanent income risk for employed households (black, solid line), Q_E, against lagged earnings rank, along with the counterfactual profile used to remove convex income risk (red, dashed line). In the counterfactual, Q_E is unchanged below the 95th percentile of lagged earnings, but is held fixed at its 95th-percentile value for households above the 95th percentile. The figure shows that the counterfactual removes the convex increase in permanent income risk at the very top of the distribution. At age 30, for example, Q_E rises from 0.100 at the 95th percentile to 0.185 at the 99th percentile and 0.290 at the top percentile; in the counterfactual, these upper-tail values are all set equal to 0.100. At age 55, the analogous values are 0.081 at the 95th percentile, 0.151 at the 99th percentile, and 0.236 at the top percentile, with the counterfactual again fixing the upper tail at the 95th-percentile value. Thus, the exercise isolates the quantitative role of convex income risk while preserving the level and shape of income risk for households below the top five percent.

Figure 29: Convex Permanent Income Risk



Note: The figure plots the permanent income risk of employed households, Q_E, by lagged earnings rank in the baseline model and in the counterfactual model that removes convex income risk. In the counterfactual, Q_E is unchanged below the 95th percentile of lagged earnings and is held fixed at its 95th-percentile value for all households above the 95th percentile. Panels (a) and (b) report the profiles at ages 30 and 55, respectively.

E.4 Additional Results: Impact of Changes in Income Risk

In this appendix, we examine the robustness of our time series results to a series of alternative estimations. We show that our results are robust to introducing lower curvature on bequests. We also examine how changes in the risk-free rate impact our estimates on the changes in wealth inequality.

Lower Curvature on Bequests. In our baseline estimation of the model, we set the curvature on bequests to be equal to the curvature on consumption. Recent work by Straub (2019) highlights that lower curvature on bequests can increase savings and generate higher top wealth shares. In this appendix, we examine the robustness of our results to putting lower curvature on bequests relative to consumption. For this exercise, we lower the curvature on bequest to 2.124 (i.e., 1 below the curvature on consumption). Table 9 presents the results of performing our time series exercise, where we set all parameters of the income process to their 2010s values, in a version of the model with lower curvature on bequests (columns (1)-(3)) and compares these results to our baseline results (columns (4)-(6)). Column (3) shows that with lower curvature on bequests, we find that the risk-free rate declines by 0.8pp, which is slightly larger than our baseline decline of 0.7pp. With lower curvature on bequests, we also get slightly larger

Table 9: Impact of Changes in Income Risk: Lower Curvature on Bequests

	(1)	(2)	(3)	(4)	(5)	(6)
	Low Bequest Curvature			Baseline Bequests		
Economy	1970*s*	2010*s*	Change	1970*s*	2010*s*	Change
Risk-free rate	3.50%	2.70%	-0.80	3.50%	2.80%	-0.70
Top 10% Wealth Share	43.40%	51.45%	+8.05	42.60%	50.11%	+7.51
Top 5% Wealth Share	30.01%	38.01%	+8.00	28.98%	36.59%	+7.61
Top 1% Wealth Share	12.44%	17.78%	+5.34	11.50%	16.60%	+5.10
Top 0.1% Wealth Share	3.24%	4.74%	+1.51	2.93%	4.26%	+1.33

Note: Table presents the results of changing income risk across the distribution between the 1970s and 2010s on measures of the risk-free rate and wealth inequality. In columns (1)-(3) we solve a version of the quantitative model where the curvature on bequests is set to 2.124, and all other model parameters are set to their values from Table 3. In columns (4)-(6), we present results from the baseline estimation of the model.

changes in wealth inequality. For example, we find that the top 1% wealth share increases by 5.34pp with lower curvature on bequests compared to 5.10pp in the baseline estimation. Thus, we conclude that our results are robust to introducing lower curvature on bequests.

Partial Equilibrium Results: Wealth Inequality. In this appendix, we examine how changes in the income process affect wealth inequality when the risk-free rate is held fixed, that is, in partial equilibrium. Table 10 presents the results. Holding the risk-free rate fixed at 3.5%, we continue to find that moving from the 1970s to the 2010s income process increases wealth concentration. However, the increase is smaller than in our baseline general equilibrium exercise. For example, the top 1% wealth share rises from 11.5% to 15.8% in partial equilibrium (column (2)), compared to 16.6% when the risk-free rate is allowed to adjust (column (3)). This comparison suggests that equilibrium movements in the risk-free rate amplify the effect of income risk on wealth inequality. In partial equilibrium, higher income risk raises precautionary saving. In general equilibrium, however, the associated increase in aggregate saving lowers the risk-free rate. This lower return reduces saving incentives, particularly outside the top decile of the wealth distribution (see panel (a) of Figure 12), and thereby amplifies the rise in wealth concentration.

Table 10: Impact of Changes in Income Risk on Wealth Inequality: Partial Equilibrium

Economy	(1) Baseline (1970*s*)	(2) 2010*s* Fixed r_f	(3) 2010*s* Clearing r_f
Risk-free rate	3.50%	3.50%	2.80%
Top 10% Wealth Share	42.60%	48.37%	50.11%
Top 5% Wealth Share	28.98%	35.00%	36.59%
Top 1% Wealth Share	11.50%	15.78%	16.60%
Top 0.1% Wealth Share	2.93%	4.06%	4.26%

Note: Table presents the results of changing income risk across the distribution between the 1970s and 2010s on measures of wealth inequality, holding the risk-free rate fixed at 3.5%. The first column corresponds to our 1970s estimation of the model. In column (2) we adjust all income process parameters to their 2010s values and hold the risk-free rate fixed at 3.5%. In column (3) we allow the risk-free rate to adjust.