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Economic insecurity and the distribution of income volatility in the United States

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ABSTRACT

We examine inequalities in the distribution of income volatility in two ways using data from the Panel Study of Income Dynamics (PSID) in order to improve our understanding of economic insecurity. First, we use a variance function regression to jointly quantify the relationship between changes in average levels of volatility as they relate to changes in the distribution of volatility. The results indicate that inequalities in the distribution of volatility rise much faster than the overall level of volatility. Therefore, what are often perceived to be rising levels of volatility for everyone are better understood as rising levels of volatility for households at the top of the volatility distribution. Second, we use a linear probability model to better understand changes in who experiences high income volatility over time. Rising inequalities in the distribution of volatility turn out to be the result of a rising probability of experiencing high volatility among households that would not typically be classified as economically insecure.

1. Introduction

The key issue of interest in this paper are changes in the distribution of income volatility that are derived from changes in the distribution of the underlying causes of income volatility, employment and family instability. Some types of employment have always been insecure, but other types, once marked by high levels of security, are now much more precarious (Kalleberg, 2009). Families with low and high levels of income and education have long been understood to have diverging destinies (McLanahan, 2004), but the power of a college degree, for example, to attain and maintain a high social position is weakening (Torche, 2011). At the same time, retrenchment of the welfare state and other sources of institutional support have altered who is eligible for protection from typical life-course risks, as well as the strength of this protection (Hacker, 2004). As a result, income volatility is rising for both individuals and families (Shin and Solon, 2011; Dynan et al., 2012). However, less attention has been paid to related changes in the distribution of income volatility itself, which are crucial to our understanding of what these rising levels mean and why they are important.

While rising income volatility is an empirical phenomenon, it is not at all clear or obvious why it or its distribution are important. According to the Permanent Income Hypothesis (PIH) (Friedman, 1957), which provides the theoretical foundation for most studies on income volatility, income volatility does not matter because short-term changes in income do not alter a person's permanent standard of living. In contrast, the modern welfare state is built on an opposing principle: income volatility does matter because it affects standards of living by reducing economic insecurity especially, but not exclusively, among vulnerable populations. The reason is that economic insecurity encourages people to shorten their time horizons and curtail saving and investing activities for individuals, families, and their children, which reduces current and future levels of standard of living (Western et al., 2012). The importance of rising income volatility and changes in its distribution are clarified when placed within the broader context of

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declining standards of living and rising economic insecurity, which are of increasing concern in society.

Income volatility is often used as a measure of economic insecurity, but there are two main drawbacks to this, especially if we want to connect it to living standards. First, the primary measure of income volatility, the standard deviation of income change in a particular study period (Gottschalk and Moffitt, 1994), is derived from the PIH. However, this measure does not distinguish income volatility from income mobility. For example, imagine two households with the same amount of income change. One household experiences income that rises each year by 10% (i.e. income mobility), while another household experiences income that fluctuates each year plus or minus 10% (i.e. income volatility). Is there a difference between these two households? According to the PIH, the answer is no, but we answer yes, there is a difference. One must distinguish volatility from mobility because income volatility increases economic insecurity, but upward mobility reduces it.

Second, if we focus on economic insecurity, then we are not only concerned with income volatility; we are also concerned with the distribution of volatility (Western et al., 2012), which is often an afterthought in most research on income volatility. Admittedly, there is good reason for this: most of what is known about the distribution of volatility is not surprising. Volatility is concentrated among the poor, the young, the single, and those with lower levels of education (Rohde et al., 2014). However, recent work has highlighted the idea that rising average levels of volatility may be better understood as the result of rising volatility at the top of the volatility distribution (Jensen and Shore, 2015). In other words, the distribution of volatility is growing more unequal or, put in a different way, the inequality of volatility is rising. If that is true, then we need to know more about the characteristics affecting who experiences high volatility, and how those characteristics change over time.

We will examine the changes over time in both the distribution of volatility and the likelihood of experiencing high volatility to provide a more complete understanding of economic insecurity. We will do this by applying the following methods to the data from the Panel Study of Income Dynamics (PSID). First, we measure volatility as the standard deviation of the residual from a household's own income trend line (Gangl, 2005; Nichols and Rehm, 2014) to distinguish the amount of income change (i.e. volatility) from the direction of income change (i.e. mobility), which is hidden in the traditional definition of volatility. Next, a variance function regression is used to jointly quantify the relationship between changes in average levels of volatility as they relate to changes in the distribution of volatility (Western and Bloome, 2009). A linear probability model is used to examine changes in the characteristics that affect who experiences high income volatility.

The results suggest that rising volatility levels are less due to everyone experiencing higher volatility and more about the distribution of volatility growing more unequal. The inequality of volatility is rising because the characteristics that increase the probability of experiencing high volatility remain constant, but the characteristics that once reduced that probability now offer less complete protection. For example, imagine two households types. One type are secure households with high levels of income and education, as well as stable employment and family life. Another type are insecure households with low levels of income and education, as well as instable employment and family life. Secure households always have a lower average volatility compared to insecure households, but the distribution of volatility is more similar within insecure households and more different within secure households. Over time, the probability of experiencing high income volatility is rising for secure households, but the probability is unchanged for insecure households. As a result, historical differences between secure and insecure households experiencing high volatility have largely disappeared.

Without denying the various interconnections, reverse causal directions, or mediating factors, getting a good education, getting and remaining married, and obtaining and staying in a good job improves access to the middle class (Sawhill et al., 2013), which ought to provide a higher standard of living with greater economic security. However, the probability of experiencing high income volatility has converged between households who did and did not follow those prescribed social norms, despite differences in their relative position in society. We will discuss the consequences of declines in relative security among those who are otherwise considered to be protected in the conclusion section, which may provide insight into rising levels of socioeconomic and political instability.

2. Background

There is clear agreement in the literature that the distribution of the underlying causes of income volatility are changing. Newfound levels of employment and family instability are now being experienced by those who were once protected due to broad changes in employment and family life, which are exacerbated by declining sources of stability. However, related changes in the distribution of who experiences what type of income change over long periods of time, which informs our understanding of economic insecurity, remain overlooked. At the same time, common measures of income volatility are not always applicable for examining issues of economic insecurity. Before we address issues of measurement, we discuss the primary factors that contribute to changes in the distribution of volatility, which inform our selection of the independent variables, as described in the variables section.

First, there is a casualization of employment relations, where the connection between employees and employers has become less secure, especially but not exclusively among those in low wage jobs (Sassen, 2006). The rise of a globalized economy has altered the demand for goods and the labor that produced them (Brady et al., 2007). Technology is a major contributing factor in the changing demand for labor, as some of the goods that once required people to manufacture them are now made by machines (Autor et al., 2003). While most attention paid to technological change has focused on its effects on middle-income, blue-collar, manufacturing jobs, other types of high-income, white-collar, and service professions once thought to be immune from automation, such as accountants and lawyers, are also being affected (Brynjolfsson and McAfee, 2011).

Further, the non-wage and salary benefits of employment, such as healthcare and pension plans, formerly provided by employers to most employees, became both less generous and more restrictive to specific positions over time (Kalleberg, 2009). As a result, there are declining levels of job security even among those with well-paying jobs (Neumark, 2000). One consequence is that volatility is rising most among the top 1% of income earners even if volatility is always higher among the bottom 10% of income earners (Hardy and Ziliak, 2014). While employment instability has long been associated with the poor and the young, instability is now experienced by those who used to be protected by their high level of income or occupational status.

A second factor is the casualization of family life, albeit with important differences across class (Cherlin, 2010). While marriage still confers many benefits, including security, the decision to marry is increasingly affected by a variety of factors. For example, both financial security and employment stability are critical for the decision to marry, but the presence of one without the other can delay the timing of marriage (Smock et al., 2005). Rising levels of income inequality and employment polarization also limit opportunities for achieving and maintaining financial security and employment stability, especially for men (Oppenheimer et al., 1997). As a result, cohabitation rates are on the rise, particularly among population groups with low levels of income or education (McLanahan, 2004). At the same time, married, two-income households with children are facing their own set of serious challenges (Warren and Tyagi, 2004). As the institution of marriage becomes less stable, the traditional concept of the family is becoming more complex. Like employment insecurity, family instability may be higher among those at the bottom of the income and educational distribution, but it is no longer restricted to those groups.

Finally, traditional sources of stability are also declining. The power of labor unions to provide wage and employment stability has become weaker, as membership declines and fewer people participate in work stoppages (Western and Rosenfeld, 2011). Religion, which is correlated to marital formation and stability, has also seen declining levels of participation (Putnam and Campbell, 2012). The contemporary welfare state is also marked by transformative change, as the institutions that formerly dampened employment and family-life instability are weakened by the process of liberalization (Streek and Thelan, 2005). As a result, the tax system, which reduces income instability for the non-poor, and the transfer system, which reduces income instability for the poor, has grown less responsive to changes in income (Hardy, 2017). In addition, the distribution of income volatility by demographic characteristics are also changing. For example, old age and high education are often thought to provide income stability, owing in part to their higher incomes and employment stability, but income volatility rose within every category of education and age between 1970 and 2008 (Dynan et al., 2012). The result of these various changes is that while instability may still be very high among groups that are often thought to be insecure (i.e., low-income, young, single, less educated, etc.), it is rising among other groups that are often thought to be secure.

Economic insecurity is a multi-faceted term that may be understood as the inability of individuals to protect themselves against economic losses resulting from employment and family instability and provide a preferred standard of living without relying on public or private subsidies (Hacker et al., 2014). Translating this idea into something that may be examined empirically is a challenge because both objective and subjective measures of economic insecurity exist (Mau et al., 2012): a subjective measure is the likelihood of future job loss, and an objective measure is income volatility. Unfortunately, the variables used to examine subjective insecurity are not always available in data sets used to examine income volatility, which is a critical component of economic insecurity (Rohde et al., 2014). Without denying the value of alternative measures, we examine the component of economic insecurity that is experienced as income volatility.

An unresolved question in the literature is how best to measure income volatility, especially in the context of economic insecurity. In the introduction, we raised concerns about using the standard deviation of income change in a study period to measure income volatility, a point we will further explore in the methods section. But other measures exist. In particular, another common measure of income volatility is the amount of change in income from one time period to the next (DiPrete and McManus, 2000; Western et al., 2016), especially the likelihood of experiencing large, downward changes (Hacker, 2006). However, this measure overlooks the degree to which long-term trends can ameliorate or exacerbate short-term changes. For example, an individual with a single, large change in income is not distinguishable from another individual with multiple, large changes in income over time, which may or may not exacerbate or offset each other. By contrast, we rely on an alternative measure of volatility that is not often used to distinguish long-term changes in income that are smooth and directional from short-term changes that are more volatile, as we describe in the methods section below.

3. Methods

We use the following three methods to isolate the various sources of change in the distribution of income volatility. First, we measure income volatility from a household's own income trend line in order to distinguish volatility from mobility (either upwards or downwards). Second, a variance function regression is used to distinguish and jointly quantify the distribution of volatility in relation to average levels of volatility. Third, a linear probability model is then used to explore changes in the characteristics affecting the probability of experiencing high levels of volatility over time. Before moving on to describe our methods, data, and variables, we acknowledge the variety of research choices outlined in these sections. Other researchers have and will continue to make other viable choices, many of which are debated in the literature. However, the results presented here are not sensitive to alternative models, samples, and variable specifications, including measurement errors, as detailed in Appendix A on sensitivity analysis.

3.1. Measuring the amount and direction of income change

The measure of volatility used here is based on a modification to the canonical model proposed by Gottschalk and Moffitt (1994), which was used to examine the relationship between income volatility and income inequality. In their model, which we refer to as the permanent income framework because it is derived from the permanent income hypothesis, y_{pit} is defined as the log of real annual earnings (y) in study period (p), which contains a given number of years, for individual (i) in year (t). Within a given study period, y_{pit} contains two parts, a permanent component that does not vary over time within individuals (β_{0pi}, i.e. the constant), and a transitory component that does (μ_{pit}, i.e. the residual). Volatility is the variance of the transitory component, which classifies all changes in income as volatile.

While the permanent income framework is appropriate for examining the relationship between income volatility and income inequality, it is not appropriate in the context of economic insecurity. The reason for this is that it does not distinguish changes in income that are smooth and directional from changes in income that are volatile. For example, if an individual experienced constant increases in wages due to an annual raise (i.e. a union contract that guarantees built-in annual increases, above and beyond the rate of inflation), then this would be measured as volatility even though the individual would experience this as upward mobility. For our purposes, it is important to distinguish the amount from the direction of income change because while income volatility increases economic insecurity, upward mobility reduces economic insecurity.

Instead, we rely upon an alternative measure of volatility, which "incorporates some more recent refinements in the empirical implementation" of the permanent income framework (Gangl, 2005). We refer to this as the income trend framework. The idea is that income change in a given study period is decomposed into three parts, not two. The first part is a person-specific constant (β_{0pi}), which is identical to the permanent component of income change, described earlier. However, the transitory component of income change is further decomposed into two parts: income trend ($\beta_{1pi}T$) and income volatility (μ_{pit}). To do so, we regress a separate, person-specific income trend onto income for each individual in each study period, as shown in model 1.

$$\log y_{pit} = \overbrace{\beta_{0pi}}^{permanent} + \overbrace{\underbrace{\beta_{1pi}T}_{trend} + \underbrace{\mu_{pit}}_{volatility}}^{transitory} \tag{1}$$

$$\text{Income mobility } (\Delta\hat{y}_{pi}) = \hat{y}_{pi,t=N} - \hat{y}_{pi,t=1}$$

$$\text{Income volatility } (\upsilon_{pi}) = \text{Standard deviation } (\mu_{pit})$$

From model 1, we are able to measure volatility and mobility for a given individual in a given study period. Volatility (υ_{pi}) is measured as the standard deviation of the within-person residual from a person-specific trend line for each person in a given study period. While income trend is not the same as income mobility, we may use the trend line to derive a measure for mobility. Mobility ($\Delta\hat{y}_{pi}$) is measured as the difference, for each person in a given study period, in the predicted income from the trend line between the first period ($\hat{y}_{pi,t=1}$) and the last period ($\hat{y}_{pi,t=N}$). In so doing, we are able to decompose income change into both amount (i.e. volatility) and direction (i.e. mobility).

3.2. Distribution of volatility

Next, we examine the relationship between trends in income volatility and the distribution of volatility using a variance function regression (VFR), as proposed by Western and Bloome (2009). While we follow the detailed code provided and described by Western and Bloome, at its most basic level, the VFR used here is a two-step regression model with individual-level fixed effects, as shown in model 2.

$$\log \upsilon_{pi} = \beta x_{pi} + \alpha_i + \varepsilon_{pi} \tag{2}$$

$$\hat{\upsilon}_{pi} = \beta x_{pi} \; (i.\ e.\ \ Average\ volatility)$$

$$\hat{\varepsilon}^2_{pi} = \lambda x_{pi} \; (i.\ e.\ \ Distribution\ of\ volatility)$$

The first step is to estimate β with a linear regression of the dependent variable, log income volatility (υ_{pi}), on our independent variables (x_{pi}), to be described later. The log transformation provides a scale-invariant measure where coefficients for the level of volatility are comparable to coefficients for the distribution of volatility. Individual-level fixed effects (α_i) are fit by subtracting person-level means from the dependent and independent variables and applying a linear regression model to the transformed variables. This yields estimates of the $\hat{\beta}$ coefficients and residuals, $\hat{\varepsilon}_{pi} = \upsilon_{pi} - x_{pi}\hat{\beta}$, which are used in the second step. The $\hat{\beta}$ coefficients are interpreted in the normal way, describing the average difference in log volatility associated with a one-unit change in a given independent variable (x_{pi}).

The second step is to estimate λ with a gamma regression of the dependent variable, the square of the difference between actual and predicted volatility (i.e. the residual) from the first step ($\hat{\varepsilon}^2_{pi}$), on those same mean-deviated independent variables (x_{pi}), using a log link function. While most social science research ignores the residual, it contains important information. The residual is the difference between actual and predicted volatility for each household in each study period. The residual yields numbers that are small and large, as well as negative and positive, but if we square the residual, then we get a positive, continuous measure of the distribution of volatility from the average, as indicated by the $\hat{\beta}$ coefficients. A gamma regression is a type of generalized linear model for positive right-skewed dependent variables. The resulting $\hat{\lambda}$ coefficients describe the average amount volatility will deviate from the average with a one-unit change in a given independent variable.

The independent variable (x_{pi}) in model 2 is $K \times 1$ vector of time-varying variables measured for upward mobility, downward mobility, income at start, a dichotomous variable for age at start (Age > 49), and period effects. Age is transformed into a dichotomous variable to capture the impact of the rising distribution of volatility among older household heads, which is obfuscated when age is a continuous variable.[1] Period effects are six dichotomous variables for the beginning of a study period that are grouped in five-year increments (study period begins 1970–1974, 1975–1979, …, 1997–2003) to compare changes in the level and distribution of volatility over time. In so doing, the VFR jointly estimates and directly compares the determinants of both the level and distribution of volatility over time.

3.3. Probability of experiencing high volatility

Last, we examine changes over time in the probability of experiencing high levels of volatility using a linear probability model (LPM) with individual-level fixed effects, as shown in model 3. The dependent variable is a dichotomous variable indicating high volatility, defined as levels of household volatility above the 90th percentile of volatility in a given study period. Estimates derived from a LPM describe the average difference in the probability (between 0 and 1) of experiencing high income volatility associated with a discrete change in a given independent variable (Wooldridge, 2012).

$$\Pr\left(v_{pi} 90^{th}\ percentile\right) = \beta_{0pi} + \beta z_{pi} + \gamma t_{pi} + \delta\left(z_{pi} \times t_{pi}\right) + \alpha_i + \varepsilon_{pi} \tag{3}$$

The independent variable (z_{pi}) in model 3 is $J \times 1$ vector of categorical variables for income, mobility, age, gender, race, and education, as well as broad changes in family and employment characteristics within any given study period, as defined below in the variables section. The continuous variables of income, mobility, and age are transformed into categorical variables in order to facilitate comparison between the continuous and categorical variables. Period effects (t_{pi}) and their interaction with each of the independent variables ($z_{pi} \times t_{pi}$) are also included in order to capture changes over time in both time-varying and -invarying characteristics that affect the probability of experiencing high levels of volatility. A time-invariant, person-specific fixed effect (α_i) is included in the model to control for unobserved selection into high levels of volatility, and to account for the fact that the same households are present across multiple study periods. Individual-level fixed effects (α_i) are fit by subtracting person-level means from the independent variables and applying a linear regression model to the transformed variables. The LPM is used to estimate changes in the characteristics that affect the probability of experiencing high income volatility over time.

4. Data

We use data from the Panel Study of Income Dynamics (PSID) between 1970 and 2013 to improve our understanding of economic insecurity by examining changes in the distribution of volatility over time. Begun in 1968 with 5,000 families, the PSID sampled original family members, their descendants, and their married partners every year through 1997, and biannually since then. With the inclusion of original PSID family members' children who have formed their own households, the survey conducted in 2013 includes data on more than 9,000 families.

While the PSID is one of the primary data sets used to examine income volatility, it is neither the only one used to examine income volatility nor economic insecurity (for example, Hardy and Ziliak, 2014 and Hardy, 2017 use the CPS, Bania and Leete, 2009 use the SIPP, and Dahl et al., 2011 use income tax records). However, the key advantage of the PSID is that we can not only examine volatility over a longer period of time, but also within a longer study period, which are essential for distinguishing volatility from mobility.

The full study period in our analysis is between 1970 and 2013, which contains 26 overlapping 11-year study periods (1970–1980, 1971–1981, …, 2003–2013). An 11-year study period enables us to distinguish between volatility and mobility (Gittleman and Joyce, 1999; Burkhauser and Couch, 2009; Bradbury, 2011), which often requires a longer study period compared to studies that focus solely on volatility. However, given the lack of agreement on what constitutes an appropriate study period (Jenkins, 2011), we have also replicated the main table of interest using a seven-year study period.

Despite the advantages of the PSID, there are disadvantages. One challenge is that the data are more representative of the United

[1] If age were included in the VFR as a continuous variable (linear, quadratic, or spline), then the coefficients on the dichotomous period variables would indicate that the distribution of volatility is declining over time, which does not match the descriptive statistics, previous research (Jensen and Shore, 2015), nor the empirical results, as shown in Table A.3 that applies model 2 to a sub-sample of younger, middle-aged, and older households. However, regardless of the age specification (dichotomous, linear, quadratic, or spline), the correlation between the raw and predicted distribution of volatility is qualitatively similar ($r = 0.20$) and, when averaged over time, suggest a somewhat left-skewed, U-shape curve over time, which is consistent with the model-adjusted period coefficients. Therefore, using a dichotomous variable for age provides a model that offers both ease of interpretation and a good fit for both the level and distribution of volatility.

States population prior to the current waves of immigration that began in the 1970s. While supplemental samples do exist, Shin and Solon (2011) have raised critical issues with each of these.[2]

We only use the Survey Research Center (SRC) sub-sample of the PSID and exclude all additional sub-samples. The appeal of the SRC sample is that we avoid the issue of sampling weights entirely, as the sample does not include any supplemental over-samples of sub-population groups, but similar results were achieved if we included the Survey of Employment Opportunity (SEO), i.e. the 'poverty' sub-sample.

Another challenge is the shift in the PSID from an annual to a biannual survey. For example, in the 11-year study period from 1997 to 2007, there are six survey periods, but in the 11-year study period from 1970 to 1980, there are 11. We use every available survey period in any given study window, but similar results were achieved if we maintain the biannual construction of the survey for study periods beginning prior to 1997.

The sample used here is restricted in the following ways, which is broadly consistent with how the PSID data are used by scholars who examine income volatility (Shin and Solon, 2011; Dynan et al., 2012; Moffitt and Gottschalk, 2012). The sample includes heads of households between the ages of 25 and 54 in the first year of the study period, are no older than 64 in the last year of the study period, and are present throughout the entire 11-year study period in the sense that they are either employed or unemployed, but looking for work, and have real, inflation-adjusted total annual family income greater than $100 and are not top-coded or missing in each year of the study period. In contrast to most studies on income volatility, which excludes women head of households owing to the fact that their rates of labor market participation are less consistent, this paper includes them, so long as they meet the criteria described above. Qualitatively similar results were achieved if observations with less than $100 of total family income in a given year were included.

The criteria described above are applied to each 11-year study period, which range in size from 902 in the study period beginning in 1970 to 1557 in the study period beginning in 2003. The resulting sample contains 32,757 household-study period observations, which includes 4048 unique households, for an average of 12.91 overlapping 11-year study periods per household, out of a possible of 26. As a result, the data are an unbalanced panel comprised of multiple balanced panels. The unique nature of the data presents a challenge for all studies of volatility over multiple years when it comes to the appropriate methods to apply or weights to use (Nichols and Rehm, 2014), but the results are not sensitive to these issues.

5. Variables

The descriptive statistics for the variables are shown in Table 1. The selection of the variables in our analysis are derived from the literature review, which connects changes in the distribution of income volatility to two key components. First, there are changes in the distribution of the underlying causes of income volatility, employment and family instability. Second, there are also changes in the distribution of volatility by household characteristics, like income, age, and education, which provide less protection over time against income volatility.

The income variable is total family income, which is inflation-adjusted to 2009 dollars using the CPI-U-RS,[3] adjusted for family size,[4] and transformed into its natural log because it is a positive, right-skewed variable that is greater than 1. Income at start is defined as the residual of income after taking out year fixed effects in a given study period (i.e. a time- or age-earnings profile),[5] as is the standard protocol in the volatility literature. As a result, average income at start, which is the average of the first two observations in a study period, is near 0 (0.105).

Income mobility is defined as the difference between the beginning and end of an 11-year study period in the predicted income from the year-adjusted trend line for each household, as shown in model 1. Downward mobility is any downward change in income less than −5%, and upward mobility is any upward change in income greater than 5%. While we define income change that rises or falls by less than five percentage points in any given 11-year study period as no income change, average income change for those who saw their income rise is 0.437 log points, which is nearly identical to the amount of income change experienced among those who saw

[2] From footnote 11 in Shin and Solon (2011): "We do not use the Survey of Economic Opportunity component (the so-called 'poverty sample') mainly because of the serious irregularities in that sample's selection. The problems recounted in Brown (1996) are too numerous to repeat here in their entirety. The problem we find most disturbing is that, for reasons that remain unknown to this day, the computer consulting firm in Washington, DC that the Office of Economic Opportunity hired to select low-income households from the Census Bureau's 1967 Survey of Economic Opportunity sample failed to include most of the eligible households in the lists it transmitted to the Survey Research Center. Worse yet, the omissions clearly were not random. Brown's memo notes a racial pattern – the transmission rate was 55% for non-whites and 21% for whites. A passage he quotes from the Survey Research Center's 1984 PSID User Guide also refers to 'substantial' variation across geographic areas. That passage concludes, 'By the time we realized that not all the addresses of the 'signers' had been forwarded, the Census personnel knowledgeable about the process had moved on to designing the 1970 Census, and OEO personnel were not able to provide us any information. Our repeated efforts to secure more information about the lost cases were not successful.'"

[3] Annual Average Consumer Price Index Research Series (CPI-U-RS) Using Current Methods All Items: 1947 to 2014. Current Population Reports. U.S. Department of Commerce Economics and Statistics Administration. Income and Poverty in the United States: 2014. P60-252.

[4] Total family income is adjusted for family size by dividing by the square root of family size.

[5] According to Gottschalk and Moffitt (2009), adjusting for an age-earnings profile is necessary, or else "aggregate growth in earnings would generate transitory deviations from an average by itself." While the definition of volatility used here renders adjusting for an age-earnings profile unnecessary because volatility is defined from a household's own income trend line in the first place, we follow the common practice in research on income volatility. The results are identical to those achieved without adjusting for an age-earnings profile.

Table 1
Descriptive statistics.

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Income characteristics (household):						
[a]Income at start (y_{pi})	32,757	45,350.710	35,852.280	26,392.910	38,071.300	54,749.270
[b]Log income at start (y_{pi})	32,757	0.000	57.805	− 33.720	1.152	36.219
[c]Change in income ($\Delta\hat{y}_{pi}$)	32,757	− 0.000	.557	− .301	.010	.321
$\Delta\hat{y}_{pi}$> 5%	15,238	.437	.355	.189	.347	.579
$\Delta\hat{y}_{pi}$< -5%	14,559	.457	.396	.181	.348	.608
[d]Income volatility (υ_{pi})	32,757	22.314	16.867	11.729	17.807	27.307
Income volatility (Log υ_{pi})	32,757	2.890	.650	2.462	2.880	3.307
High income volatility ($\upsilon_{pi} > 90^{th}$ pct)	32,757	.100	.300	0	0	0
Demographic characteristics (head):						
Male	32,757	.912	.283	1	1	1
White	32,757	.917	.276	1	1	1
Less than HS	32,757	.117	.321	0	0	0
HS	32,757	.339	.473	0	0	1
More than HS	32,757	.545	.498	0	1	1
Older (Age > 49)	32,757	.079	.269	0	0	0
Family characteristics (In a study period):						
Always single	32,757	.125	.330	0	0	0
Marital change	32,757	.166	.372	0	0	0
Always married	32,757	.710	.454	0	1	1
Never kids	32,757	.422	.494	0	0	1
Sometimes kids	32,757	.211	.408	0	0	0
Always kids	32,757	.367	.482	0	0	1
Employment characteristics (In a study period):						
Ever unemployed	32,757	.346	.476	0	0	1
Ever self employed	32,757	.309	.462	0	0	1
Total N	32,757					
Unique N	4048					
Avg. study periods per unique N	12.91					

[a] The average of the first two-observations in a study period. Income is family size adjusted.
[b] The residual of log income after taking out year fixed effects in a given study period for the first year of a given study period.
[c] Where $\Delta\hat{y}_{pi} = \hat{y}_{pi,t=N} - \hat{y}_{pi,t=1}$ if.$\hat{y}_{pit} = \beta_{0i} + \beta_{1i}T$
[d] Where υ_{pi} = Standard deviation (μ_{pit}) if.$\log y_{pit} = \beta_{0pi} + \beta_{1pi}T + \mu_{pit}$

their incomes decline (0.457 log points). Alternatively, one could define mobility as the raw or unadjusted difference in log income between the beginning and end of the study period, but the results are not dependent on the particular definition of mobility used here.

Demographic characteristics are race, gender, education, and age of the household head. 91.7% of the sample is white, and 91.2% of the sample is male. Age is a dichotomous variable indicating older workers (Age > 49), who account for 7.9% of the sample. 54.5% have more than a high school diploma, 33.9% have a high school diploma, and 11.7% have less than a high school diploma.

Family characteristics are defined by broad categories of stability and instability in marital status and children in the household during a study period. Marital status is categorized as: always married, never married, or marital change. Marital change collapses into one category household heads who either exited or entered a marriage, or both. The majority of the sample are always married (71.0%), with 12.5% always single, and the remaining 16.6% experiencing marital change at some point in a given study period. Children status refers to always having children in the household, never having children in the household, or sometimes having children in the household. Sometimes children collapses into one category households with children who exited or entered the household during a study period, or both. 42.2% never have children, 36.7% always have children, and 21.1% experience children entering and/or leaving the household during a study period.

Employment characteristics are also defined by broad categories of employment stability or instability of the household head in a given study period. Never unemployed is a dichotomous variable indicating whether or not the household head experienced more than 40 or more hours of unemployment (or 1 week) in a given study period. 34.6% of household heads were never unemployed. Ever self-employed is a dichotomous variable indicating whether or not the household head worked for themselves in a given study period. 30.9% of household heads were self-employed at some point in a given period.

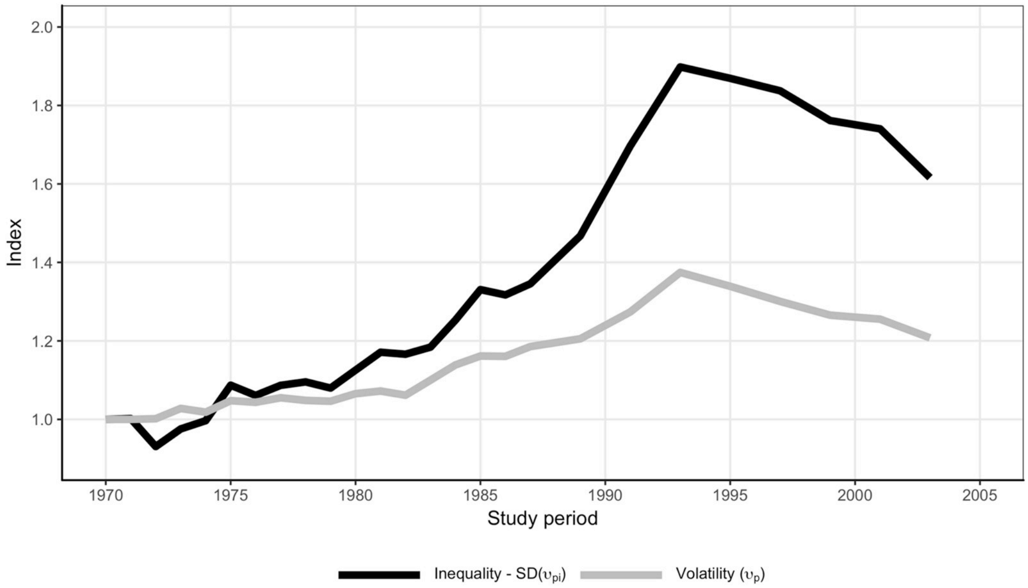


Fig. 1. Index of trends in income volatility and distribution of volatility.

The dependent variable of income volatility is defined in two ways, owing to our two models that result from our two empirical questions. In the variance function regression, income volatility is transformed into its natural log in order to have a scale-invariant measure for the average and distribution of volatility, as discussed in the methods section. Log volatility is 2.890, meaning household income deviates by about 3% from the trend line, on average, across all study periods. Alternatively, one could measure volatility as the standard deviation of income change in a study period, as Gottschalk and Moffitt originally proposed, but the results are not dependent on the definition of volatility used here, so long as one controls for mobility. In the linear probability model, high income volatility is defined as a dichotomous variable indicating volatility above the 90th percentile in any given 11-year study period. Therefore, 10% of all households in the sample have levels of volatility above the 90th percentile.

6. Results

Descriptive trends for income volatility and the distribution of volatility, as measured by the standard deviation of income volatility, over time are shown in Fig. 1. Values are indexed to the study period beginning in 1970 in order to facilitate comparison. Income volatility rose nearly 40% from the early 1970s through the mid-1990s, but then declined slightly afterwards, such that volatility in the study period beginning in 2003 is about 20% higher than the study period beginning in 1970. The distribution of volatility also rose from the early 1970s through the mid-1990s, rising nearly 90%, but then declined slightly afterwards, such that the distribution of volatility in the study period beginning in 2003 is about 60% higher than the study period beginning in 1970. A rising distribution of volatility is interpreted as a distribution that is growing more unequal. Put in a different way, the inequality of volatility is rising.

A comparison of the descriptive trend lines indicates that inequalities in the distribution of volatility are rising much faster than average levels of volatility. Therefore, rising levels of volatility are primarily the result of certain households at the top of the volatility distribution experiencing higher levels of volatility rather than rising levels of volatility throughout the distribution. The obvious next question is who are these households, which we will examine in the next subsection. To give a preview, the results suggest that rising inequalities in the distribution of volatility are driven by a rising probability of high volatility among households not often classified as insecure.

6.1. Distribution of volatility

The results of the variance function regression formally quantify the relationship between the distribution of volatility and the level of volatility, as shown in Table 2. In order to provide a robustness check, we have replicated Table 2 using a variety of alternative model and sample specifications, as shown in Table A.2 in Appendix A.

The β coefficients indicate average levels of volatility. Positive β coefficients indicate rising levels of volatility. The λ coefficients indicate the distribution of volatility, or how far levels of volatility fall from the average. Positive λ coefficients indicate rising

Table 2
Determinants of average level of income volatility and the distribution of volatility, parameter estimates from a variance function regression with fixed effects.

	Average (β)	Distribution (λ)
Downward mobility ($\Delta\hat{y}_{pi} < -5$)	0.351(0.008)	− 0.231(0.045)
Upward mobility ($\Delta\hat{y}_{pi} > 5$)	0.165(0.010)	− 0.094(0.052)
Income at start	− 0.136(0.010)	0.074(0.052)
Older (Age > 49)	− 0.002(0.011)	0.431(0.052)
Study period beginning:		
1975 − 1979	0.012(0.008)	− 0.306(0.043)
1980 − 1984	0.026(0.009)	− 0.274(0.047)
1985 − 1989	0.108(0.010)	− 0.216(0.053)
1990 − 1996	0.140(0.012)	0.192(0.059)
1997 − 2003	0.064(0.013)	0.293(0.065)
Constant	− 0.000(0.002)	− 2.001(0.011)
Observations	32,757	32,757
R^2	0.063	

Note:Standard errors in parenthesis.

inequality of volatility. As detailed in the methods section, the β coefficients are comparable to the λ coefficients because the dependent variable in the first step of the variance function regression is the log of income volatility, which allows us to measure the relative value of one to the other.

We begin at the bottom of the table in order to examine the time trends in volatility and the distribution of volatility. The five study periods beginning in 1970–1974 are the reference group. The β coefficients for the period effects indicate that average levels of volatility rose 14% from the early 1970s through the mid-1990s, but then declined slightly afterwards. The λ coefficients for the period effects indicate that inequalities in the distribution of volatility declined 22% from the early 1970s through the late-1980s, but then rose afterwards. If we compare λ coefficients for study periods beginning between 1997 and 2003 to the study periods beginning 1970–1974, then the inequality of volatility rose by about 30% over the entire study period. The time trends mirror the descriptive results shown in Fig. 1, which confirm that the inequality of volatility is rising much faster than the level of volatility.

Next, we examine the other variables in the model in order to quantify where the inequality is coming from. If we look at income, the β coefficient indicates that each unit of increase in log income decreases income volatility by −0.136 log points. This is consistent with the well-established fact that volatility is concentrated among the poor.

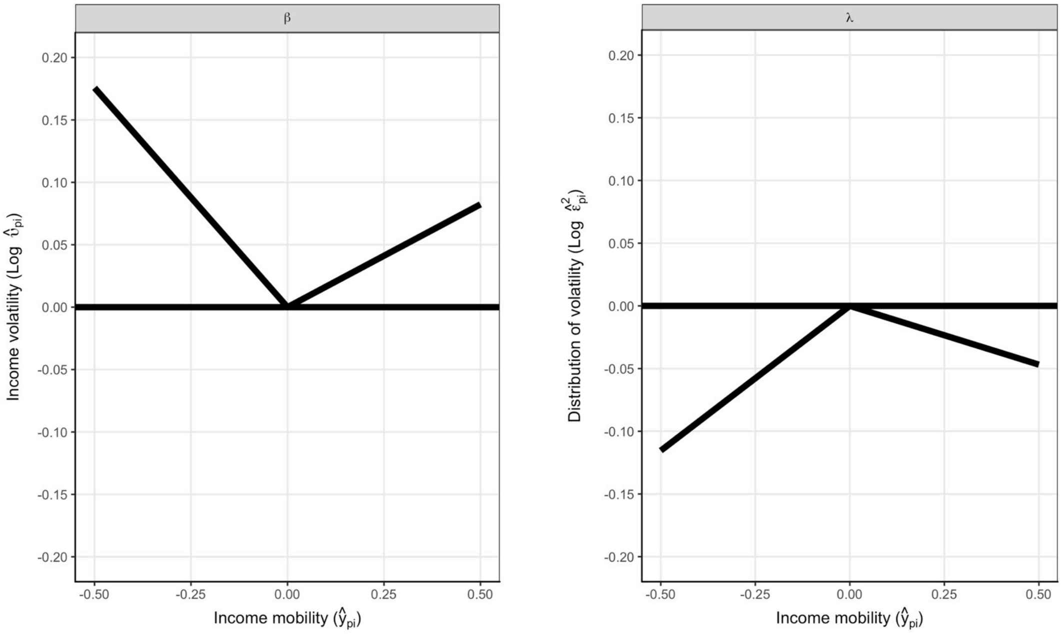
The comparable λ coefficients indicate that each unit of increase in log income increases the inequality of volatility by 0.074 log points. A positive λ coefficient means that the difference between (1) the actual level of volatility a household experiences and (2) the average level of volatility among those households with comparable incomes, rises with income.

What does it mean that average levels of volatility decline with income, but inequality of volatility rises with income? While we discuss the broader implications regarding economic insecurity below, the specific answer has two components. First, high-income households have lower average levels of volatility compared to low-income households. Second, levels of volatility are more similar within low-income households and more different within high-income households. As a result, low-income households experience more volatility, but there is less variety of these experiences among them. By contrast, high-income households experience less overall volatility, but there is more variety of these experiences among them. We will see this idea repeated as we examine the age and mobility variables in Table 2.

The β coefficient for older workers indicates that income volatility is lower (−0.2%) for older workers than it is for younger workers. This is consistent with the idea that volatility is concentrated among younger workers. However, the comparable λ coefficient indicates that the inequality of volatility from the average is 43.1% higher for older workers than younger workers. Similar to income, levels of volatility decline with age, but the inequality of volatility rises with age.

The relationship between income volatility and income mobility shown in Table 2 may be easier to understand in graphical form, as shown in Fig. 2. If we look at the mobility characteristics, then the β coefficients indicate that volatility rises both when income mobility is rising and falling. The finding that volatility rises in conjunction with mobility (upward and downward) makes sense because there are greater, more frequent changes in income. However, if we compare the β coefficient for upward mobility (0.165) to downward mobility (0.351), then the level of volatility among those whose incomes are declining is twice as high as those whose incomes are rising. Therefore, downward mobility is much more volatile than upward mobility.

The comparable λ coefficients for the mobility characteristics are both negative. However, if we compare the λ coefficient for upward mobility (−0.094) to downward mobility (−0.231), then we reveal asymmetries in the relationship between the direction of income mobility and the distribution of income volatility. The negative coefficients mean individuals with large amounts of income



(a) Average volatility (b) Distribution of volatility

Fig. 2. Relationship between the level and distribution of volatility and mobility, as shown in Table 2. Note: Graph illustrates the impact of a percentage change in income mobility on the level and distribution of income volatility from Table 2, if all other continuous variables are at their average values and the categorical variables are at their baseline values.

mobility (upward or downward) experience levels of volatility that are more similar to each other than individuals with small amounts of income mobility. However, even though the coefficients are both negative, the fact that the coefficient for downward mobility is larger than upward mobility means that those who experience upward mobility have more varied (i.e. less similar) levels of volatility than those who experience downward mobility.

In summary, the results from the variance function regression suggest two key implications. First, the inequality of volatility is rising much faster over time than the average level of volatility. Therefore, the source of rising average volatility at the population level is better understood as rising levels of volatility of particular households at the top of the volatility distribution. Second, despite the fact that younger and low-income households, as well as those that experience downward mobility, are characterized by higher average levels of volatility, the distribution of volatility is higher among high-income, older, or upwardly mobile households. Therefore, the source of rising inequality of volatility is the result of high levels of income volatility experienced by particular households within groups that are often thought to be more secure.

In broader terms, the relationship between volatility and its distribution can be interpreted as a reflection of differences in the absolute insecurity between groups and the relative insecurity within groups. Compared to the respective reference group, high income, upward mobility, and old age characteristics have lower levels of absolute insecurity, owing to lower average levels of volatility between groups, but higher levels of relative insecurity, owing to a higher distribution of volatility from the average within groups. We will return to this idea in the discussion section.

6.2. Probability of experiencing high volatility

The results from the linear probability model quantify the probability of experiencing high levels of income volatility over time. High volatility is defined as levels of volatility above the 90th percentile in any given study period. While complete results from the model are shown in Table A.4 in the Appendix, we present them here in graphical form in order to facilitate interpretation, as shown in Fig. 3. The graph illustrates the predicted coefficients and the standard errors of the interaction for each independent variable and study period after factoring out the main effects for time period, which are fixed at 10%.[6] Despite the fact that there is a large amount of noise, there are also clear patterns in the probability of experiencing high income volatility. The graph presents the probability for all characteristics, but the key ideas are described below.

We begin with the income characteristics. Households in the lowest income quartile always have the highest probability of

[6] While the point estimates on time period are non-zero, the standard errors are large, double or even triple the standard error on any other coefficient, and include 0, which is the expected impact over time on the probability of experiencing high income volatility in a given period of time.

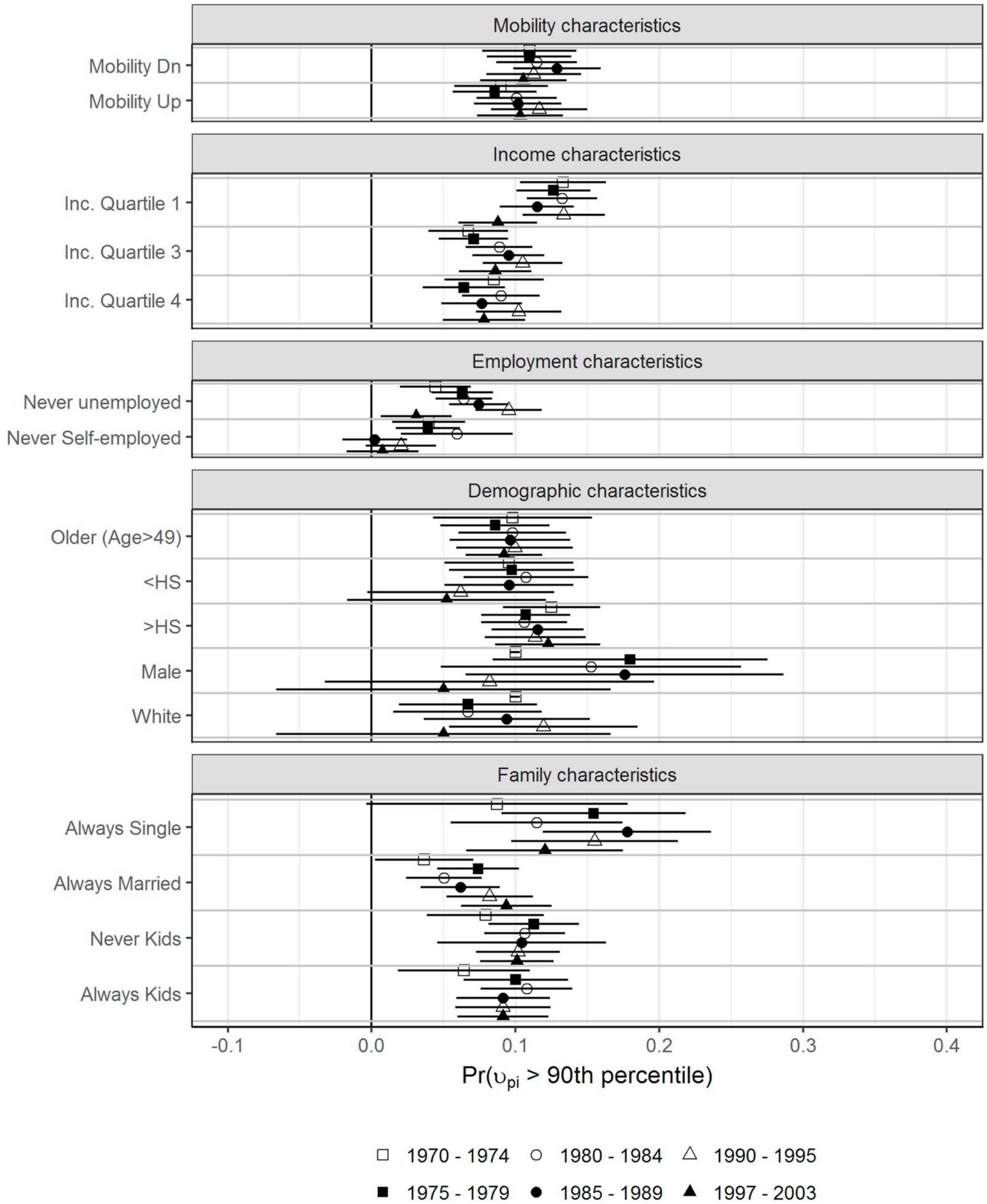


Fig. 3. Determinants of experiencing high income volatility over time, predicted estimates from linear probability models with fixed effects, as shown in Table A.4. Note: Graph illustrates the predicted probability of experiencing high income volatility from model 3, as shown in Table A.4. The interpretation is change over time within each category in the probability of high income volatility relative to the reference category. For example, the reference category for always single or always married is change in marital status.

experiencing high income volatility. By contrast, those in the fourth income quartile always the lowest probability. However, the relative probability is constant over time for those in the bottom income quartile, but is rising over time for those in the top income quartile. Therefore, high income provides relatively less protection over time against the probability of experiencing high income volatility than it once did, even if the absolute probability is always lower.

Next, we examine the mobility characteristics, which convey a similar idea as the income characteristics. Households that experience downward mobility always have a higher probability of experiencing high-income volatility and households that experience

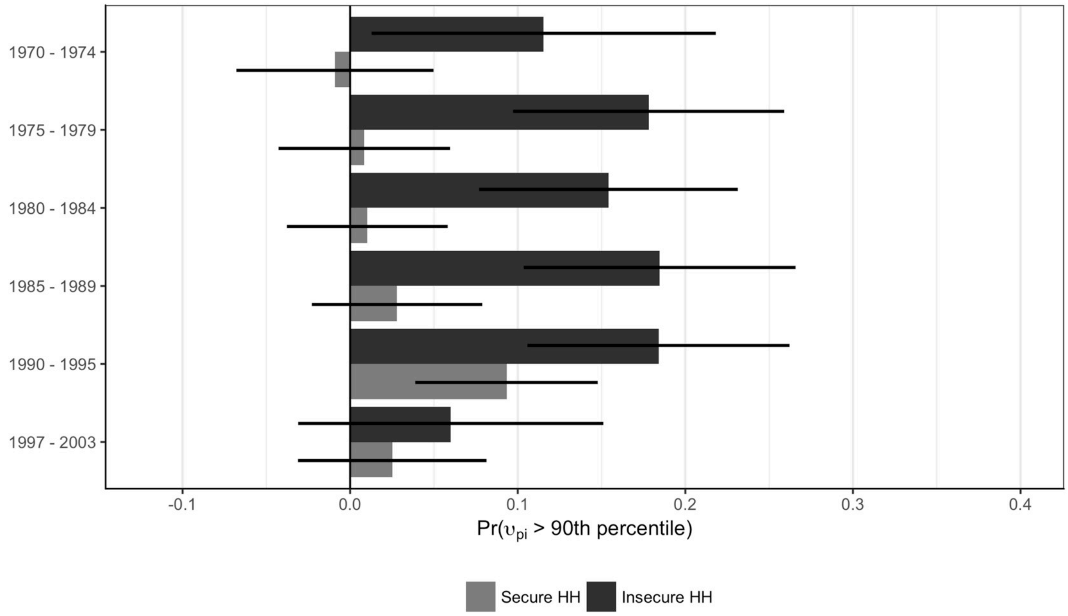


Fig. 4. Index of trends in income volatility and distribution of volatility. Note: Graph illustrates the predicted probability of experiencing high income volatility over time by household characteristics from linear probability models with fixed effects, as shown in Table A.4, which is derived from model A.4. Controlling for gender, race, age, children in the household, self-employment, and mobility, which are set to their baseline values, "Secure HH" is defined as a household that is always married, has a high level of education (> HS), is in the top income quartile, and never unemployed. "Insecure HH" is defined as a household that are always single, has a low level of education (< HS), is in the bottom income quartile, and has experienced unemployment.

upward mobility always have a lower probability. However, the relative probability is constant over time for those who experience downward mobility, but is rising over time for those who experience upward mobility. Therefore, like high income, upward mobility now provides less protection over time against the probability of experiencing high income volatility than it once did, even if the absolute probability is always lower.

The impact of never being unemployed in a study period always reduces the probability of experiencing high income volatility relative to households that have experienced unemployment, as we would expect. However, with the exception of the last period, the probability of experiencing high volatility rises over time for those that have never experienced unemployment relative to households that have. Therefore, the relative protection provided by stable employment against the probability of experiencing high income volatility is declining.

Regarding education, the probability of experiencing high income volatility has declined over time for those with low levels of education and risen over time for those with high levels of education, especially after the mid-1970s. Therefore, the more education you have, the more likely you are to experience high income volatility, meaning the protection once offered by high education has declined over time.

Regarding the family, households that are always married always have a lower probability of experiencing high income volatility compared to households that are always single, as we would expect. However, the relative probability is rising over time. Therefore, the relative protection provided by marital stability is declining.

6.3. Economic insecurity and income volatility

To provide a clearer connection between economic insecurity and income volatility, we computed the predicted probability of experiencing high income volatility over time for two distinct household types, as shown in Fig. 4. The first household type is classified as secure: always married, has high levels of education (> HS) and income (top quartile), and is never unemployed. The second household type is classified as insecure: always single, has low levels of education (< HS) and income (bottom quartile), and has experienced unemployment. All other control variables are set to their baseline values.

As expected, insecure households always have a higher probability of experiencing high income volatility relative to the secure households. However, over time, up until the last period of analysis, the relative probability remains unchanged for insecure households. At the same time, the probability rises for secure households from nearly 0 to 10%. In the last period of analysis, the probability of experiencing high income volatility fell for both the secure and insecure households, to the point that share a similar probability. A detailed look at Fig. 3 indicates the role of low education and always single for secure households, and never unemployed for insecure households. While the last period is clearly different, the broader conclusion remains the same: what were clear differences in the probability of experiencing high income volatility between secure and insecure household types have gradually, but clearly disappeared over time (see Fig. 4).

7. Summary and discussion

Before discussing the broader significance of the results, we want to highlight two key empirical contributions of our analysis. First, inequalities in the distribution of volatility are rising faster than average levels of volatility. The result is consistent with previous research (Jensen and Shore, 2015), but our contribution is the ability to compare trends in the level and distribution of volatility to each other using a variance function regression. As a result, what are often perceived to be rising levels of volatility for everyone are better understood as rising levels of volatility for households at the top of the volatility distribution (i.e. the right tail is becoming thicker). Therefore, the concern is less about rising volatility in general, but rather changes in which households experience high levels of volatility over time.

The second empirical contribution is that the characteristics affecting the probability of experiencing high income volatility are changing over time. The main characteristics that increase the probability generally remain constant (i.e. marital and employment instability), but, at the same time, the characteristics that once reduced the probability now offer less protection (i.e. marital and employment stability). Therefore, previous differences in the probability of experiencing high income volatility between secure and insecure households have disappeared because the probability is rising among households that are not typically classified as insecure.

In order to interpret the meaning and significance of the results, we return to the permanent income hypothesis (PIH), which serves as the theoretical foundation for most explorations of income volatility. The PIH assumes that short-term changes in income (i.e. volatility) do not alter a person's permanent standard of living. Taken as a behavioral theory of consumption patterns, the PIH provides a good empirical measure for standard of living, but its meaning is dependent on the amount of stability in a society (DiPrete, 2002). For example, an individual who obtains a higher level of education will orient their lifestyle to the long-term expected standard of living (i.e. permanent income) associated with that level of human capital, not to the level of income in their youth, nor income in a given year (Sørensen, 2000). However, as instability rises in a society, the ability to predict, with relative accuracy, the standard of living associated with a given amount of human capital declines.

Rising instability affects everyones level of economic insecurity, but the impact is not distributed equally. Structural inequalities in labor market, family, and welfare state institutions have created and maintained a system where some parts of society always had and continue to have higher levels of insecurity, and other parts of society were and are more protected. While it is well understood that these institutions have changed over time (Levy and Temin, 2007; Cherlin, 2014), it is not well understood how these changes have affected the distribution of economic insecurity that is experienced as income volatility. Examining changes in the distribution of who experiences how much income volatility reveals that relative insecurity is rising much more among those who were once protected, even if absolute insecurity is lower.

These results pose the following question: should society be concerned that the relative probability of experiencing high volatility is rising among those with relatively high levels of economic security? To think about answering that question, we assume a general relationship between income volatility, economic insecurity, and standard of living. Even though levels of insecurity interact with the life-course, household, and welfare regimes to make some more vulnerable and others more secure, a life defined by high levels of income volatility and economic insecurity is associated with a lower standard of living for individuals and families.

On the one hand, the answer to the question is no, we should not be too worried. The probability of experiencing high income volatility is only a concern when it is concentrated among the most insecure. The reason is that secure households are comparably better able to maintain their standard of living in the face of large, short-term changes in income relative to insecure households. On the other hand, the answer is yes, we should be concerned. The probability of experiencing high income volatility is also a concern when it is rising among those who are secure. The reason for this is that security is relative to expectation. Those who might otherwise expect a low level of insecurity owing to a high standard of living, as derived from high income and education as well as stable employment and family life, are experiencing levels of insecurity that are markedly higher than they once were.

Studying the various interconnected consequences of new groups experiencing relative insecurity represents an important area of future research. Differences in the probability of experiencing high volatility between those who did and did not follow prescribed social norms regarding work and family life are increasingly converging, despite great differences in their relative positions in society. Recent evidence suggests that more people feel like working hard and following the rules are not getting them anywhere (Hochschild, 2016; Morduch and Schneider, 2017). Non-realized growth is understood here as feelings of self-perceived deprivation, which reduces relative standard of living. Declines in relative standard of living may reduce levels of institutional trust and be mobilized by extreme political ideologies, especially among those in otherwise high-status positions who have the most resources to engage in politics. A formal link has not yet been established between economic insecurity, standard of living, and political instability, but standard of living is connected to political instability through the mechanism of generalized trust (Freitag and Bhlmann, 2009; Ruth and Yves, 2014). Therefore, beyond the empirical results, a more general contribution – derived from exploring changes over time in who experiences income volatility, and at what levels – has the potential to improve our understanding of the instability that is increasingly visible in so many aspects of modern political, economic, and social life.

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A Appendix

We compare the sensitivity of the main findings across a variety of alternative model specifications and sample selections in order to measure the robustness of the results, as shown in Table 2. Without discounting the importance of these issues, the results are qualitatively similar and do not alter the main findings.

Regarding model specifications, we acknowledge a potential challenge with the use of a fixed-effects model as it is applied here. As mentioned in the data section, the total sample from 1970 to 2013 is an unbalanced panel comprised of multiple, overlapping balanced panels, which presents a challenge in choosing the appropriate model to use, as well as which weights to apply. Despite the advantages of a fixed effects model, it ignores households that are only in the sample in a single, 11-year study period, i.e. 'singletons.' Of the 4048 unique households in the sample, there are 488 individuals who are only present in one 11-year study period, which represents 12% of the sample.

One alternative to a fixed effects model is a pooled OLS regression, which includes singletons, but ignores the panel structure completely. Another alternative is a random effects model, which addresses the issue of autocorrelation and would include singletons, but at the cost of assuming that unobserved heterogeneity will not bias the estimates. The assumption of no unobserved heterogeneity is a strong assumption and one of the main reasons why fixed effects models are often preferred over random effects when using panel data (Halaby, 2004). Alternative models that use either pooled OLS or random effects models yield qualitatively similar findings as the fixed effects model.

There is no uniform agreement on how to address issues of measurement error in income, especially at the top and the bottom of the distribution. Like us, most studies transform income into log form and drop observations where income is below $1 or $100, or top coded in a given year in a given study period of varying years. If the goal is to examine income volatility among households whose labor market participation is constant, then this makes sense. However, if the goal is to examine income volatility among all households, then there is no reason to drop observations with zero income in a given year and in a given study period. In fact, there is a strong reason to include them: households who move from zero to non-zero income account for a large proportion of all income volatility (Winship, 2011). Unfortunately, total family income was bottom coded by the PSID at $1 prior to 1994; after 1994, total family income can be negative. As a result, it is possible to include 0 and negative earnings, beginning in 1994, but not before. Therefore, we have two possible options to address measurement issues in income.

One option is to assume that the results are biased because so much volatility occurs at the bottom of the income spectrum. Therefore, it might be preferable to include very low incomes, including zero, by using a threshold of income below some particularly low amount. Jensen and Shore (2015) bottom code inflation-adjusted income by replacing values of income below $5150 with that lower bound, which is the amount of income earned if an individual worked part-time (1000 h per year) at minimum wage ($5.15 per hour) in 2005 in any given year. While the decision to include or exclude zero earnings in a given year or, alternatively, the appropriate bottom code to choose is important, qualitatively similar results are found if we include or exclude all income earners who earn below $5150 in any given year.

Another option is to assume that the results are biased due to measurement error at the top and bottom of the distribution. At the top, the PSID sets a top-code to ensure confidentiality, such that incomes above a certain point are recoded to that value. However, the top code has changed over time. Years prior to 1982 have a top-code of $99,999 after which the top-code rises to $9,999,999. At the bottom of the distribution, some households report very low earnings, some of which are real, but others of which are misreported. A common method to address issues at the very top and bottom of the distribution is to drop incomes at the top and bottom 1% and only include households in the inner 98% of the distribution (Gottschalk and Moffitt, 2009).

In addition, as mentioned in the text, we have also rerun the models including the Survey of Employment Opportunity (SEO), i.e. 'poverty' sub-sample, as well as maintaining the biannual construction of the survey for study periods beginning prior to 1997.

Regarding variable specifications, we have also rerun the models including alternative measures of both mobility and volatility that are derived from the income trend framework. While this framework seeks to distinguish the mobility from the volatility that exists within income mobility, it is not dependent on a particular measure of volatility or mobility as long as one incorporates *some* measure of volatility and *some* measure of mobility. One could define volatility as the standard deviation of income in a study period, similar to Gottschalk and Moffitt, or one could define mobility as the raw difference in income between the beginning and end of the study period. Given that both measures of volatility and mobility are highly correlated ($r = 0.9$), respectively, it is not surprising that the results are robust to both alternative variable specifications.

Another broad issue is that the idea that downward mobility is more volatile than upward mobility, which is less known. Some may argue that a basic knowledge of how earnings evolve over the life course might predict something similar, even if it has not been shown before. For example, upward mobility is more likely to be concentrated among young workers who are moving up, into the labor market while downward mobility is more likely to be concentrated among older workers who are moving down, out of the labor market. Further, upward mobility is more likely to be smooth because it is associated with raises, which tend to be more stable while downward mobility is more likely to be volatile because it is associated with job loss, which tend to be less table. Therefore, younger workers who experience more upward mobility ought to experience less volatility and older workers who experience more downward mobility ought to experience more volatility. There is no doubt that volatility follows clear life course patterns, but volatility has long been shown to be concentrated among the young and decline with age (Gottschalk and Moffitt, 1994). At the same time, previous research did not incorporate a measure for the direction of income change, as we do here. Given the clear expectations of changes in volatility over the life course, Table A.3 replicates Table 2 in stepwise form, including and/or excluding the variables for age and/or mobility, as well as the full model for a subset of younger, middle, and older household heads. Not only is downward mobility more volatile than upward mobility, but mobility may be an important mechanism that explains the negative association between age and volatility.

Table A.1
Key for Table A.2.

Model	Label	Description
1	FE	From Table 2
2	RE	Random effects model
3	POLS	Pooled Ordinary Least Squares model
4	Biannual	All 11-year study periods only include data from every other year in order to be consistent with the biannual structure of the PSID after 1997. For example, the 11-year study period between 1970 and 1980, includes data 6 periods of time (1970, 1972, 1974, 1976, 1978, 1980).
5	Bottom code	All observations with total household income below \$5150 are included and given that value
6	Top and bottom code	Exclude the top and bottom 1% of total household earnings
7	SRC/SEO	Includes both SRC (population representative) sample and SEO (poverty) oversample
8	7yr period	7 year study periods (1970–1976, 1971–1977, …, 2005–2013)
9	Alt. Mobility	Mobility is from unadjusted trend: if Δy_{0pi} = difference between average income (LN) in the last 2 years of a study period and the first 2 years of a study period.
10	Alt. Volatility	Volatility is the standard deviation of income change in a study period

Table A.2
Determinants of income volatility and distribution of volatility, parameter estimates with alternative specifications (as compared to Table 2)

	(1)		(2)		(3)		(4)		(5)		(6)
	FE		RE		POLS		Biannual		Bottom code		Keep 1% $<y_i<$ 99%
	β	λ	β	λ	β	λ	β	λ	β	λ	β
Downward mobility ($\Delta\hat{y}_i < -5$)	0.351	−0.231	0.449	−0.239	0.733	−0.209	0.399	−0.123	0.321	−0.268	0.328
	(0.008)	(0.045)	(0.008)	(0.037)	(0.009)	(0.025)	(0.010)	(0.039)	(0.009)	(0.045)	(0.010)
Upward mobility ($\Delta\hat{y}_i > 5$)	0.165	−0.094	0.244	−0.314	0.536	−0.241	0.184	−0.051	0.137	−0.148	0.111
	(0.010)	(0.052)	(0.009)	(0.042)	(0.010)	(0.027)	(0.012)	(0.045)	(0.010)	(0.050)	(0.011)
Income start	−0.136	0.074	−0.171	−0.219	−0.146	0.034	−0.172	0.001	−0.128	0.075	−0.151
	(0.010)	(0.052)	(0.007)	(0.035)	(0.006)	(0.015)	(0.013)	(0.049)	(0.010)	(0.049)	(0.011)
Old age (Age > 49)	−0.002	0.431	−0.011	0.175	0.028	0.052	0.002	0.297	−0.003	0.448	−0.018
	(0.011)	(0.052)	(0.011)	(0.043)	(0.012)	(0.030)	(0.013)	(0.047)	(0.011)	(0.051)	(0.012)
Study period beginning:											
1975 – 1979	0.012	−0.306	0.023	−0.232	0.015	0.057	0.003	−0.132	0.015	−0.311	0.012
	(0.008)	(0.043)	(0.008)	(0.037)	(0.010)	(0.028)	(0.010)	(0.039)	(0.008)	(0.042)	(0.008)
1980 – 1984	0.026	−0.274	0.046	−0.016	0.029	0.152	0.016	−0.120	0.034	−0.267	0.028
	(0.009)	(0.047)	(0.009)	(0.040)	(0.010)	(0.028)	(0.011)	(0.043)	(0.009)	(0.046)	(0.009)
1985 – 1989	0.108	−0.216	0.117	0.210	0.088	0.222	0.066	−0.040	0.119	−0.199	0.097
	(0.010)	(0.053)	(0.010)	(0.043)	(0.011)	(0.029)	(0.012)	(0.047)	(0.010)	(0.051)	(0.010)
1990 – 1995	0.140	0.192	0.165	0.974	0.124	0.505	0.127	0.063	0.145	0.196	0.105
	(0.012)	(0.059)	(0.011)	(0.046)	(0.012)	(0.030)	(0.014)	(0.053)	(0.012)	(0.058)	(0.012)
1997 – 2003	0.064	0.293	0.080	1.245	0.057	0.537	0.118	0.053	0.066	0.316	0.034
	(0.013)	(0.065)	(0.011)	(0.048)	(0.011)	(0.028)	(0.016)	(0.059)	(0.013)	(0.064)	(0.013)
Constant	−0.000	−2.001	2.755	−5.390	2.579	−1.246	−0.000	−1.571	−0.000	−1.983	−0.000
	(0.002)	(0.011)	(0.009)	(0.044)	(0.008)	(0.022)	(0.003)	(0.010)	(0.002)	(0.010)	(0.002)
R^2	0.058		0.416		0.178		0.052		0.049		0.041
Observations	32,757		32,757		32,757		33,124		32,984		30,419
Unique Observations	4048		4048		4048		3616		3593		3438

	(6)	(7)		(8)		(9)		(10)	
	Keep 1% $<y_i<$ 99%	SRC & SEO		7 year study period		Alt. mobility		Alt. volatility	
	λ	β	λ	β	λ	β	λ	β	λ
Downward mobility ($\Delta\hat{y}_i < -5$)	−0.162	0.316	−0.191	0.504	−0.117	0.401	−0.290	0.759	−0.352
	(0.052)	(0.007)	(0.038)	(0.009)	(0.034)	(0.009)	(0.051)	(0.006)	(0.049)
Upward mobility ($\Delta\hat{y}_i > 5$)	−0.140	0.118	−0.101	0.331	−0.181	0.175	−0.081	0.747	−0.604
	(0.058)	(0.008)	(0.045)	(0.011)	(0.038)	(0.011)	(0.060)	(0.007)	(0.055)
Income start	0.018	−0.157	0.063	−0.158	−0.049	−0.149	0.108	0.002	−0.204
	(0.058)	(0.008)	(0.044)	(0.011)	(0.037)	(0.011)	(0.055)	(0.007)	(0.055)
Old age (Age > 49)	0.408	0.009	0.414	0.021	0.190	−0.003	0.442	0.011	0.290
	(0.054)	(0.009)	(0.047)	(0.012)	(0.038)	(0.011)	(0.053)	(0.008)	(0.056)
Study period beginning:									
1975 − 1979	−0.282	0.011	−0.263	0.002	−0.131	0.012	−0.301	0.005	−0.302
	(0.043)	(0.006)	(0.036)	(0.010)	(0.036)	(0.008)	(0.043)	(0.006)	(0.046)
1980 − 1984	−0.269	0.025	−0.216	0.002	−0.106	0.025	−0.276	−0.002	−0.237
	(0.048)	(0.007)	(0.040)	(0.011)	(0.039)	(0.009)	(0.048)	(0.007)	(0.051)
1985 − 1989	−0.185	0.091	−0.137	0.039	−0.083	0.108	−0.216	0.047	−0.118
	(0.054)	(0.008)	(0.045)	(0.012)	(0.042)	(0.010)	(0.053)	(0.008)	(0.056)
1990 − 1995	0.209	0.111	0.232	0.109	0.271	0.146	0.186	0.090	0.307
	(0.060)	(0.010)	(0.052)	(0.013)	(0.046)	(0.012)	(0.059)	(0.009)	(0.063)
1997 − 2003	0.345	0.040	0.346	−0.089	0.692	0.077	0.282	0.048	0.362
	(0.067)	(0.011)	(0.058)	(0.016)	(0.053)	(0.013)	(0.066)	(0.010)	(0.070)
Constant	−2.060	−0.000	−2.090	−0.000	−1.359	−0.000	−2.004	0.000	−2.541
	(0.011)	(0.002)	(0.009)	(0.002)	(0.008)	(0.002)	(0.011)	(0.002)	(0.011)
R^2		0.052		0.079		0.059		0.388	
Observations		47,857		44,770		32,757		32,757	
Unique Observations		5771		4598		4048		4048	

Notes: Standard errors in parentheses.

Table A.3
Determinants of income volatility and distribution of volatility, parameter estimates with alternative age specifications (as compared to Table 2)

	Stepwise regression						Age (< 35)		Age (35–44)		Age (>= 45)	
	(1)		(2)		(3)		(4)		(5)		(6)	
	β	λ	β	λ	β	λ	β	λ	β	λ	β	λ
Downward mobility ($\Delta\hat{y}_{pi} < -5$)			0.354	−0.215	0.351	−0.231	0.250	−0.128	0.217	−0.225	0.183	0.484
			(0.008)	(0.046)	(0.008)	(0.045)	(0.012)	(0.099)	(0.013)	(0.120)	(0.017)	(0.197)
Upward mobility ($\Delta\hat{y}_{pi} > 5$)			0.169	−0.098	0.165	−0.094	0.055	−0.017	0.040	−0.001	−0.056	−0.153
			(0.010)	(0.052)	(0.010)	(0.052)	(0.014)	(0.113)	(0.015)	(0.129)	(0.022)	(0.251)
Income start	−0.045	−0.023	−0.135	0.067	−0.136	0.074	−0.191	0.121	−0.080	0.145	−0.191	−0.329
	(0.008)	(0.040)	(0.010)	(0.052)	(0.010)	(0.052)	(0.014)	(0.115)	(0.016)	(0.141)	(0.021)	(0.245)
Old age (Age > 49)	0.008	0.465			−0.002	0.431						
	(0.012)	(0.055)			(0.011)	(0.052)						
Study period beginning:												
1975 – 1979	0.010	−0.347	0.011	−0.254	0.012	−0.306	−0.053	−0.137	0.047	−0.243	−0.040	−0.294
	(0.008)	(0.045)	(0.008)	(0.043)	(0.008)	(0.043)	(0.011)	(0.088)	(0.013)	(0.117)	(0.016)	(0.179)
1980 – 1984	0.017	−0.307	0.024	−0.191	0.026	−0.274	−0.096	−0.146	0.074	−0.106	−0.024	−0.115
	(0.009)	(0.050)	(0.009)	(0.046)	(0.009)	(0.047)	(0.013)	(0.108)	(0.018)	(0.152)	(0.022)	(0.248)
1985 – 1989	0.094	−0.222	0.105	−0.113	0.108	−0.216	−0.119	0.088	0.191	−0.088	0.046	0.002
	(0.010)	(0.055)	(0.010)	(0.051)	(0.010)	(0.053)	(0.016)	(0.130)	(0.020)	(0.175)	(0.028)	(0.317)
1990 – 1995	0.126	0.146	0.136	0.326	0.140	0.192	−0.183	0.285	0.254	0.113	0.089	0.690
	(0.012)	(0.061)	(0.011)	(0.057)	(0.012)	(0.059)	(0.021)	(0.170)	(0.024)	(0.204)	(0.035)	(0.398)
1997 – 2003	0.031	0.277	0.058	0.490	0.064	0.293	−0.297	0.277	0.234	0.251	0.012	0.905
	(0.013)	(0.067)	(0.012)	(0.061)	(0.013)	(0.065)	(0.026)	(0.212)	(0.027)	(0.231)	(0.038)	(0.434)
Constant	−0.000	−1.950	−0.000	−1.997	−0.000	−2.001	−0.000	−2.536	−0.000	−2.586	−0.000	−2.631
	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.019)	(0.003)	(0.022)	(0.003)	(0.037)
R^2	0.010		0.058		0.058		0.048		0.034		0.024	
Observations	32,757		32,757		32,757		14,315		11,584		6858	
Unique Observations	4048		4048		4048		2891		751		406	

Notes: Standard errors in parentheses.

Table A.4
Determinants of experiencing high income volatility over time, parameter estimates from a linear probability model with fixed effects, as shown in Fig. 3

Variables	β
Income mobility:	
Downward mobility ($\Delta\hat{y}_{pi} < -5$)	0.010(0.018)
Downward mobility x 1975 − 1979	− 0.000(0.023)
Downward mobility x 1980 − 1984	0.005(0.023)
Downward mobility x 1985 − 1989	0.020(0.024)
Downward mobility x 1990 − 1996	0.003(0.025)
Downward mobility x 1997 − 2003	− 0.004(0.024)
Upward mobility ($\Delta\hat{y}_{pi} > 5$)	− 0.011(0.017)
Upward mobility x 1975 − 1979	− 0.005(0.023)
Upward mobility x 1980 − 1984	0.011(0.023)
Upward mobility x 1985 − 1989	0.012(0.024)
Upward mobility x 1990 − 1996	0.028(0.025)
Upward mobility x 1997 − 2003	0.014(0.024)
Income quartile at start:	
Income quartile 1	0.035(0.016)
Income quartile 1 × 1975 − 1979	− 0.007(0.019)
Income quartile 1 × 1980 − 1984	− 0.001(0.020)
Income quartile 1 × 1985 − 1989	− 0.019(0.021)
Income quartile 1 × 1990 − 1996	0.001(0.022)
Income quartile 1 × 1997 − 2003	− 0.048(0.022)
Income quartile 3	− 0.035(0.015)
Income quartile 3 × 1975 − 1979	0.004(0.019)
Income quartile 3 × 1980 − 1984	0.023(0.019)
Income quartile 3 × 1985 − 1989	0.029(0.020)
Income quartile 3 × 1990 − 1996	0.040(0.021)
Income quartile 3 × 1997 − 2003	0.020(0.020)
Income quartile 4	− 0.016(0.018)
Income quartile 4 × 1975 − 1979	− 0.022(0.021)
Income quartile 4 × 1980 − 1984	0.005(0.022)
Income quartile 4 × 1985 − 1989	− 0.009(0.023)
Income quartile 4 × 1990 − 1996	0.018(0.024)
Income quartile 4 × 1997 − 2003	− 0.007(0.024)
Demographic characteristics:	
White	
White x 1975 − 1979	− 0.035(0.026)
White x 1980 − 1984	− 0.035(0.028)
White x 1985 − 1989	− 0.006(0.031)
White x 1990 − 1996	0.020(0.035)
White x 1997 − 2003	0.021(0.037)
Male	
Male x 1975 − 1979	0.084(0.051)
Male x 1980 − 1984	0.055(0.056)
Male x 1985 − 1989	0.080(0.059)
Male x 1990 − 1996	− 0.019(0.062)
Male x 1997 − 2003	− 0.053(0.062)
Older (Age > 49)	− 0.002(0.030)
Older x 1975 − 1979	− 0.013(0.033)
Older x 1980 − 1984	− 0.000(0.035)
Older x 1985 − 1989	− 0.002(0.037)
Older x 1990 − 1996	0.002(0.037)
Older x 1997 − 2003	− 0.006(0.033)

(continued on next page)

Table A.4 *(continued)*

Education:	
Less than HS	− 0.005(0.024)
Less than HS x 1975 − 1979	0.002(0.020)
Less than HS x 1980 − 1984	0.012(0.022)
Less than HS x 1985 − 1989	− 0.004(0.029)
Less than HS x 1990 − 1996	− 0.035(0.035)
Less than HS x 1997 − 2003	− 0.046(0.037)
More than HS	0.026(0.018)
More than HS x 1975 − 1979	− 0.019(0.016)
More than HS x 1980 − 1984	− 0.020(0.017)
More than HS x 1985 − 1989	− 0.010(0.019)
More than HS x 1990 − 1996	− 0.012(0.020)
More than HS x 1997 − 2003	− 0.003(0.021)
Employment characteristics:	
Never unemployed	− 0.059(0.013)
Never unemployed x 1975 − 1979	0.020(0.015)
Never unemployed x 1980 − 1984	0.021(0.016)
Never unemployed x 1985 − 1989	0.032(0.017)
Never unemployed x 1990 − 1996	0.054(0.018)
Never unemployed x 1997 − 2003	− 0.014(0.019)
Never self-unemployed	− 0.064(0.014)
Never self-unemployed x 1975 − 1979	− 0.001(0.014)
Never self-unemployed x 1980 − 1984	− 0.021(0.015)
Never self-unemployed x 1985 − 1989	− 0.040(0.016)
Never self-unemployed x 1990 − 1996	− 0.020(0.018)
Never self-unemployed x 1997 − 2003	− 0.034(0.018)
Family characteristics:	
Always single	− 0.014(0.049)
Always single x 1975 − 1979	0.071(0.049)
Always single x 1980 − 1984	0.029(0.053)
Always single x 1985 − 1989	0.095(0.055)
Always single x 1990 − 1996	0.072(0.056)
Always single x 1997 − 2003	0.035(0.055)
Always married	− 0.067(0.018)
Always married x 1975 − 1979	0.039(0.020)
Always married x 1980 − 1984	0.015(0.021)
Always married x 1985 − 1989	0.026(0.022)
Always married x 1990 − 1996	0.048(0.024)
Always married x 1997 − 2003	0.060(0.024)
Never kids	− 0.022(0.022)
Never kids x 1975 − 1979	0.035(0.023)
Never kids x 1980 − 1984	0.029(0.025)
Never kids x 1985 − 1989	0.022(0.026)
Never kids x 1990 − 1996	0.024(0.026)
Never kids x 1997 − 2003	0.023(0.025)
Always kids	− 0.038(0.025)
Always kids x 1975 − 1979	0.038(0.026)
Always kids x 1980 − 1984	0.046(0.028)
Always kids x 1985 − 1989	0.029(0.029)
Always kids x 1990 − 1996	0.029(0.030)
Always kids x 1997 − 2003	0.029(0.030)
Study period beginning:	
1975 − 1979	− 0.111(0.071)

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Table A.4 *(continued)*

1980 – 1984	– 0.071(0.076)
1985 – 1989	– 0.110(0.081)
1990 – 1996	– 0.095(0.084)
1997 – 2003	0.023(0.085)
Constant	0.100(0.002)
Observations	32,757
R^2	0.011

Note: Standard errors in parenthesis.

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