FROM THE PEAKS TO THE VALLEYS: CROSS-STATE EVIDENCE ON INCOME VOLATILITY OVER THE BUSINESS CYCLE

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Abstract—Countercyclical variation in individuals' idiosyncratic labor income risk could generate substantial welfare costs. Following past research, we infer income volatility—the variance of permanent income shocks, a standard proxy for income risk—from the rate at which cross-sectional variances of income rise over the life cycle for a given cohort. Our novelty lies in exploiting cross-state variation in state economic conditions or state sensitivity to national economic conditions. We find that income volatility is higher in good state times than bad; during good national times, we find volatility is higher in states that are more sensitive to national conditions.

I. Introduction

THE welfare cost of business cycles is of natural interest to macroeconomists. Our intuition is that welfare is substantially lower in recessions than in booms and that, holding average growth fixed, welfare would be improved if boom and bust cycles were eliminated.[1] However, simple representative-agent models typically do not generate large welfare losses in recessions because average consumption does not fall very far in bad times (Lucas, 1987, 2003).

Moving away from a representative-agent setting, a large literature has explored models with business cycle variation in idiosyncratic risk (Díaz–Giménez, 1997; Millard, Sensier, & Scott, 1997; Storesletten, Telmer, & Yaron, 2001; Schulhofer-Wohl, 2008; Krusell et al. 2009; Constantinides & Duffie, 1996). Idiosyncratic income risk could generate a substantial welfare cost of business cycles.[2] Past empirical tests of this hypothesis have focused on macro moments (Casteñeda, Díaz-Giménez, & Ríos-Rull, 1998; Díaz-Gíménez, Quadrini, & Ríos-Rull, 1997; Jaimovich & Siu, 2009) or national conditions (Storesletten, Telmer, and Yaron, 2004). We estimate the cyclicality of income volatility by pairing cross-state variation with tight identifying restrictions. We find evidence that income volatility is higher when state economic conditions are good than when they are bad.

Documenting cyclical variation in idiosyncratic income risk faces two major challenges. First, sample sizes are small in the sense that panel data sets—best suited to estimate income volatility, a commonly used proxy for income risk—typically have observations on relatively few people. Second, sample sizes are small in the sense that data span few business cycles. This makes it difficult, if not impossible, to differentiate business cycle effects from other trends—for example, the New Deal in the 1930s, the war on poverty in the 1960s (Goldin & Margo. 1992), or the large rise in income inequality since 1970. In this case, results will be particularly sensitive to time and cohort controls and also to the clustering of standard errors.

To overcome the first problem (small samples in panel data), we exploit Deaton and Paxson's (1994) technique of inferring the variance of permanent income changes from the rate at which the cross-sectional variance of income grows over the life cycle for a given cohort. As in Storesletten et al. (2004), who find higher idiosyncratic income volatility in national recessions using cross-sectional features of data from the Panel Study of Income Dynamics, we compare cohorts whose work lives spanned greater and fewer numbers of recessions. We thus identify results from cross-sectional data, in our case using millions of individual-level observations from a 1% subsample of the U.S. Census. If the variance of income changes is greater in recessions than in booms, the cross-sectional variance of income will be higher in cohorts whose work lives spanned more recessions.

To overcome the second problem (too little variation over time in national economic conditions), we exploit cross-state variation in economic conditions such as state GDP growth. Such variation is substantial (Owyang, Piger, & Wall, 2005; Frank, 2009; Crone, 2005), so we can identify our results while controlling for all national variation as well as much state-specific variation. In particular, we do not restrict the dispersion of initial ability within a birth state cohort, and we allow each state its own baseline variance of permanent income shocks. Results are identified by comparing the rate at which cross-sectional variance grows over time within a state-level cohort during better-than-average or worse-than-average economic conditions for that state. This contrasts with Storesletten et al. (2004) who use national data. Variation in economic conditions is limited in national data, so strong identifying restrictions are required; in particular, the age profile of residual wage inequality is assumed to have the same shape for all cohorts.

In exchange for the added richness of state-level variation, we confront the problem of cross-state migration. Americans frequently move across state lines, often in response to economic conditions (Blanchard & Katz, 1992; Rosenbloom & Sundstrom, 2004). We define cohorts based on year and state

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[1] If the relationship between economic conditions and welfare is convex so that recessions are "more bad" than booms are good, there are welfare gains from eliminating business cycles holding average economic conditions fixed.

[2] First, the variance of individuals' permanent shocks to income could vary over the business cycle, with more risk in bad times (when wealth levels are lower and absolute risk aversion is higher) than good (Acemoglu & Scott, 1994; Mukoyama & Şahin, 2006). Second, the variance of idiosyncratic shocks could be higher (throughout the business cycle) in economies with more pronounced boom-bust cycling (Davis & Haltiwanger, 1992; Krebs, 2003; Barlevy, 2004).

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of birth to ensure that moving does not drive our results. This may understate our effect because individuals who leave their birth state may not experience the economic conditions we assign to them. In section IVD, we show that results are robust to handling interstate migration in a variety of ways.

The goal of this paper is to use cross-state variation to examine whether idiosyncratic income volatility is higher when economic conditions are good or bad. Of course, economic conditions may not be one-dimensional; conditions may be good in some dimensions but not in others. A priori, there is no reason that the relationship between economic conditions and income volatility must be the same for all measures of economic conditions. Furthermore, we have no strong theory about the most relevant measure of economic conditions for this purpose. For this reason, we examine a variety of measures: state-level GDP growth, NBER recessions and national GDP growth (interacted with cross-state differences in sensitivity to national conditions), and predicted employment shocks (using nationwide industry-specific shocks and cross-state differences in exposure to these). Using such state-level variation, we find that the cross-sectional variance of income is higher when these measures of past economic conditions have been good. This implies that income volatility—the variance of income changes—is higher in good times than bad. Our finding with state-level variation and flexible controls differs from Storesletten et al.'s (2004) result using nation-level variation. We consider two possible (not mutually exclusive) explanations for this difference.

First, results based on state-based or nationwide variation rely on different identifying restrictions; the failure of these restrictions may bias state-based results, nationwide results, or both. In section IVD (and online appendix C), we show that state-based results are quite robust to identifying restrictions (controls) and variation (sample). However, section IVA shows that nationwide results are quite sensitive to both specification and sample; this is not particularly surprising given the small amount of nationwide variation available in the data. We consider a variety of possible explanations (other than countercyclical idiosyncratic risk, such as the rise in inequality in the 1970s) for the nationwide cross-sectional patterns in the data.

Second, state-level economic conditions may simply affect income risk differently than nationwide economic conditions do. Nationwide recessions may coincide with more risk, while state-level "recessions" may coincide with less. We attempt to rule out this possibility by examining cross-state variation in exposure to national economic conditions. We find that in states with greater sensitivity to national economic conditions, the cross-sectional variance of income is higher when past national economic conditions have been good. If we are willing to assume that business cycle variation in income risk is most pronounced in states that experience national business cycles more intensely, this implies that the variance of permanent income changes is higher in good (national) times.

II. Empirical Strategy

We consider the cross-sectional implications of a standard process for individual labor income. The income process follows Hall and Mishkin (1982), Carroll and Samwick (1997), and many others in including permanent and transitory shocks. Following Guvenen (2007, 2009), we allow heterogeneous income growth rates. Y_{it}, the labor income in year t of individual i who begins work in year $c \leq t$, is given by

$$\ln(Y_{it}) = g(X_{it}) + a_i + b_i(t-c) + \Sigma_{r=c+1}^{t} \rho^{t-r}\omega_{ir} + \varepsilon_{it}. \tag{1}$$

g is the predictable (to the econometrician with covariates, X_{it}) component of income; for example, income may differ by age, calendar year, education, race, or their interactions. y_{it} refers to excess log income, $y_{it} \equiv \ln(Y_{it}) - g(X_{it})$. Individual i begins work with a person-specific initial (persistent) income (a_i) and income growth rate (b_i). We follow Guvenen in assuming that a_i and b_i are fixed at the beginning of work life (c).

Individuals are hit with permanent shocks (ω_{it}), which damp out at rate $\rho \leq 1$.[3] They are also hit with transitory shocks (ε_{it}). Transitory shocks and permanent shocks are i.i.d. with mean zero and variances $\sigma^2_{\varepsilon,it} \equiv E\left[\varepsilon^2_{it}\right]$ and $\sigma^2_{\omega,it} \equiv E\left[\omega^2_{it}\right]$, respectively. We call $\sigma^2_{\omega,it}$ and $\sigma^2_{\varepsilon,it}$ the permanent and transitory variance or volatility. The aim of this paper is to use cross-sectional data on income to identify the impact of economic conditions in state s at time t (e_{st}) on the permanent (and transitory) variance.

Consider the set of individuals born in state s in birth year cohort c (they begin their work life in year c, for example, at age 25). For the moment, we ignore the possibility that individuals change their state of residence, though we consider this possibility at length in section IVD. We assume that (a) the variances of shocks are the same for all observations from a given state, cohort, and year ($\sigma^2_{\omega,it} = \sigma^2_{\omega,sct}; \sigma^2_{\varepsilon,it} = \sigma^2_{\varepsilon,sct}$), and (b) individuals' shocks are uncorrelated with one another. We show the implications of relaxing the assumption of no correlation in online appendix B. When incomes evolve according to equation (1) for all individuals, the cross-sectional variance of excess log income for state s and cohort c in year t is then

$$\begin{aligned}\operatorname{var}(y_{it}|sct) = {} & \sigma^2_{a,sc} + 2\sigma_{ab,sc}(t-c) + \sigma^2_{b,sc}(t-c)^2 \\ & + \sigma^2_{\varepsilon,sct} + \Sigma_{r=c+1}^{t} \rho^{2(t-r)}\sigma^2_{\omega,scr}.\end{aligned} \tag{2}$$

The cross-sectional variance of excess log income (var $(y_{it}|sct)$) depends on five parameters: the variance of initial income ($\sigma^2_{a,sc} \equiv \operatorname{var}(a_i|sc)$), the variance of income growth rates ($\sigma^2_{b,sc} \equiv \operatorname{var}(b_i|sc)$), the covariance between initial income and income growth rates ($\sigma_{ab,sc} \equiv \operatorname{cov}(a_i, b_i|sc)$), the

[3] The model is estimated for various values of ρ, which can be estimated from panel data. We use $\rho = 1$ as our focal value for simplicity and vary ρ in our robustness checks.

transitory variance ($\sigma^2_{\varepsilon,sct}$), and the permanent variance ($\sigma^2_{\omega,sct}$, for $t > c$). Critically for identification, the cross-sectional variance of income grows with age for a given cohort as permanent shocks ($\sigma^2_{\omega,sct}$) accumulate.[4] As some receive good shocks and others receive bad shocks, incomes will spread out.

Three of these parameters ($\sigma^2_{a,sc}, \sigma_{ab,sc}, \sigma^2_{b,sc}$) vary by state ($s$) and cohort ($c$); two of them ($\sigma^2_{\omega,sct}, \sigma^2_{\varepsilon,sct}$) vary by state ($s$), cohort ($c$), and year ($t$ or equivalently age $t-c$). Clearly, restrictions are needed to use the cross-sectional variance (var ($y_{it}|sct$)) to understand how the permanent variance ($\sigma^2_{\omega,sct}$) varies with economic conditions (e_{st}).[5]

When using national data (dropping state subscripts), our baseline restrictions are

$$\rho = 1;\ \sigma^2_{a,c} = \alpha_a;\ \sigma_{ab,c} = \sigma^2_{b,c} = 0, \tag{3a}$$

$$\sigma^2_{\omega,ct} = \alpha_{\omega,t-c} + \beta_\omega e_t;\ \sigma^2_{\varepsilon,ct} = \alpha_{\varepsilon,t-c} + \beta_\varepsilon e_t. \tag{3b}$$

In this case, plugging equations (3a) and (3b) into equation (2) reduces to

$$\begin{aligned}\text{var}\,(y_{it}|ct) = {} & \left(\alpha_a + \alpha_{\varepsilon,t-c} + \Sigma^t_{r=c+1}\alpha_{\omega,r-c}\right) \\ & + \beta_\varepsilon e_t + \beta_\omega \Sigma^t_{r=c+1} e_r,\end{aligned} \tag{4}$$

which can be estimated with

$$\text{var}\,(y_{it}|ct) = \Sigma_{t-c}\,(\beta_{t-c} \times 1_{t-c}) + \beta_\varepsilon e_t + \beta_\omega \Sigma^t_{r=c+1} e_r. \tag{5}$$

The first term in equations (4) and (5) allows a flexible age profile for the cross-sectional variance; this age profile captures the initial dispersion of income (α_a), as well as an age profile in the transitory and permanent variances ($\alpha_{\varepsilon,t-c}$ and $\alpha_{\omega,t-c}$, respectively). The second term allows the transitory variance to vary with economic conditions, linking current economic conditions and the current cross-sectional variance of income. The third term allows the permanent variance to vary with economic conditions, linking past economic conditions to the current cross-sectional variance of income. Note that we have to place strong restrictions on the model to identify β_ω; in particular, we must assume that the age profile of the cross-sectional variance is the same (or, in robustness checks, similar) for all cohorts across the sample period.[6]

We overcome this limitation of national data by exploiting intranational variation. Identification with richer controls follows from assuming that some effects do not vary by state. When we use cross-state variation, our baseline restrictions are

$$\rho = 1;\ \sigma^2_{a,sc}\text{unrestricted};\ \sigma_{ab,sc} = \sigma^2_{b,sc} = 0, \tag{6a}$$

$$\sigma^2_{\omega,sct} = \alpha_{\omega,ct} + \alpha_{\omega,s} + \beta_\omega e_{st};\ \sigma^2_{\varepsilon,sct} = \alpha_{\varepsilon,ct} + \alpha_{\varepsilon,s} + \beta_\varepsilon e_{st}. \tag{6b}$$

From the second element of equation (6a), birth cohorts in each state may differ flexibly in their initial dispersion of income. Critically, all nationwide cohort-time variation in permanent and transitory variance can be completely flexible ($\alpha_{\omega,ct}$ and $\alpha_{\varepsilon,ct}$; see equation [6b]).[7] When we plugging equations (6a) and (6b) into equation (2), the cross-state analog to equation (4) can be written as

$$\begin{aligned}\text{var}\,(y_{it}|sct) = {} & \sigma^2_{a,sc} + \left(\alpha_{\varepsilon,ct} + \Sigma^t_{r=c+1}\alpha_{\omega,cr}\right) \\ & + \left(\alpha_{\varepsilon,s} + \alpha_{\omega,s}(t-c)\right) + \beta_\varepsilon e_{st} \\ & + \beta_\omega \Sigma^t_{r=c+1} e_{sr}.\end{aligned} \tag{7}$$

This can be estimated with the cross-state analog of equation (5):

$$\begin{aligned}\text{var}\,(y_{it}|sct) = {} & \Sigma_s \Sigma_c \left(\sigma^2_{a,sc} \times 1_s \times 1_c\right) \\ & + \Sigma_t \Sigma_c \left(\alpha_{t,c} \times 1_t \times 1_c\right) \\ & + \Sigma_s \left(1_s \times \left(\alpha_{\omega,s}(t-c)\right)\right) \\ & + \beta_\varepsilon e_{st} + \beta_\omega \Sigma^t_{r=c+1} e_{sr}.\end{aligned} \tag{8}$$

The first term in equations (7) and (8) controls for birth year cohort effects separately for each state; the initial dispersion of income is not restricted. The second term allows flexible nationwide variation in (permanent and transitory) volatility, as well as heterogeneity over time and across cohorts. The third term (first term on second row) allows cross-state variation in the rate at which the cross-sectional dispersion of income grows over the life cycle; this accounts for the possibility that conditions in a particular state (for example, its endowment of natural resources) create both positive economic conditions and fast growth in cross-sectional moments throughout the sample.

The impact of state economic conditions (e_{st}) on the permanent variance (β_ω) is identified within states from the final term, comparing the cross-sectional variance of income at times with better-than-average (for that state) versus worse-than-average past performance. We also consider specifications in which identification comes from variation between states and from variation both between and within states. Despite this rich set of controls, many degrees of freedom remain. As outlined in online appendix A, the number of degrees of freedom is increasing in the number of states we

[4] This is true only to the degree that "permanent" shocks are fairly permanent, $\rho \approx 1$. Otherwise, only recent shocks affect the current cross-sectional variance.

[5] With data from S states, C cohorts, and T years (per cohort), we have $S \times C \times T$ observations of the cross-sectional variance (var ($y_{it}|sct$)), but without additional restrictions, $3 \times S \times C + 2 \times S \times C \times T \gg S \times C \times T$ parameters to estimate.

[6] Results for this baseline specification are shown in the first column of table 2. We also consider linear trends in $\sigma^2_{a,c}$ (second column of table 2), an unrestricted $\sigma^2_{\varepsilon,ct}$ (third column of table 2), which is estimated by adding year fixed effects; and an unrestricted $\sigma^2_{a,c}$ (fourth column of table 2), which is estimated by adding cohort fixed effects. We allow alternative values for ρ in table C.7 in the online appendix.

[7] While we estimate this baseline model in the body of this paper, appendix B in the online supplement shows the implication of more flexible income dynamics that allow for less-than-unit-root permanent shocks and heterogeneous income growth rates; appendix C shows results given this setup.

TABLE 1.—SUMMARY STATISTICS

Observation (birth state × birth year × census year) Characteristics	N	Mean	S.D.	5th	95th
Variance of excess $\ln(Y)$	2,352	0.455	0.128	0.257	0.661
Variance of $\ln(Y)$	2,352	0.534	0.154	0.294	0.783
Proportion receiving bottom code	2,352	0.022	0.024	0.002	0.062
Variance of excess $\ln(Y_{WAGE})$	2,352	0.962	0.263	0.555	1.400
Proportion receiving bottom code	2,352	0.135	0.078	0.056	0.305
Variance of excess $\ln(Y_{FAM})$	2,352	0.383	0.110	0.233	0.568
Proportion receiving bottom code	2,352	0.014	0.021	0	0.049
Number of individuals in observations	2,352	4,385	4,634	315	15,261
Proportion now living in birth state	2,352	0.576	0.118	0.371	0.748
Economic Conditions					
	First Year	Mean	S.D.	5th	95th
Years of NBER recession	1890	0.310	0.465	0	1
Years of negative national growth	1890	0.233	0.424	0	1
% of year in recession	1890	0.265	0.355	0	1
National GDP growth	1891	0.035	0.057	−0.064	0.139
ln(Stock Return)	1926	0.072	0.197	−0.322	0.336
Years of negative state growth	1964	0.268	0.443	0	1
State GDP Growth	1964	0.019	0.040	−0.044	0.079
State Employment Prediction	1940	0.007	0.029	−0.044	0.059
ln(State Stock Return)	1926	0.074	0.227	−0.375	0.393
Cohorts' Average Experience over Work Life					
	National Cohorts				
	N	Mean	S.D.	5th	95th
Years of NBER recession	18	0.208	0.085	0.067	0.371
Years of negative national growth	18	0.165	0.111	0.000	0.343
% of year in recession	18	0.164	0.075	0.058	0.305
National GDP growth	18	0.035	0.006	0.023	0.048
	State Cohorts				
	N	Mean	S.D.	5th	95th
Years of negative state growth	672	0.241	0.124	0	0.450
State GDP growth	672	0.021	0.010	0.009	0.037
State employment prediction	864	0.007	0.007	−0.002	0.022

See the text for the data sources for the national and economic data and the construction of the state stock returns and state employment prediction. In each of seven Census interview years, seven age groups (equivalently, seven five-year birth cohorts) are observed in each of 48 states (excludes Hawaii, Alaska, and Washington, DC), generating 2,352 observations. Average experience over the work life refers to a (birth state)×(birth year) cohort's average annual economic conditions, where the average is taken over conditions from ages 20–24 to 54–59 where possible, and otherwise over the years covered by our data (1926+ for stocks, 1940+ for employment, 1964+ for state GDP). For four of eighteen birth year cohorts, we have no observations of state GDP information.

include. This appendix also shows the number of times—and years—in which each cohort is observed, as well as the ages at which each cohort is observed.

III. Data

A. Income Data

Income data are from the U.S. Census 1% subsample in each decade from 1950 to 2000 and from the American Community Survey in 2005.[8] We restrict the sample to male household heads ages 25 to 59 who are in the labor force (employed or unemployed, ignoring those out of the labor force). We form eighteen national (birth year) cohorts based on five-year birth year bins; these are described in detail in online appendix A.

When we examine state-level variation, we subdivide national cohorts into state cohorts. These are formed on (birth state)×(five-year birth year) bins. Given the income process we assume (see equation [1]), we can infer volatility from the cross-sectional variance only if cohort composition remains stable. For this reason, we form state cohorts based on birth state and not current state of residence.[9] As shown in the top panel of table 1, slightly more than half of individuals we consider are living in their birth state at the time we observe their income. Provided we examine within-cohort variation over time (to control for possible selection into birth states), changes in the cross-sectional

[8] Data on the industry of each worker are available from 1920 to 2000 in the Census and for 2005 in the ACS.

[9] Individuals may change their state of residence (in response to economic conditions in the states from which and to which they are moving, (Blanchard & Katz, 1992; Rosenbloom & Sundstrom, 2004), but they cannot change their state of birth. While this solves selection problems related to moving, other types of selection may be possible. We exclude workers who are out of the labor force (neither employed nor unemployed), a group that could in theory be differentially affected across states. Results are qualitatively similar whether such workers are included (as unemployed). Individuals who die before age 59 are also selected out of the sample. Even if death rates were correlated with economic conditions (as described in Ruhm, 2000, 2003, 2005, 2007; Miller, Page, Stevens, & Filipski, 2009), death rates in this age group are far too low to affect our results.

variance will reflect income volatility and not selection. Of course, moving away from states with poor economic conditions to states with good economic conditions provides a natural buffer against changes in state-specific economic conditions (Blanchard & Katz, 1992). As such, our state-level results understate the magnitude of the impact of unavoidable, national-level variation in economic conditions on income volatility.[10]

Except where otherwise specified, income is defined as individual pretax income from all sources including assets (*inctot*).[11] Income data are sometimes negative or 0; we cannot simply exclude individuals with negative or 0 income, because economic conditions affect the proportion of zeros. For example, if individuals with 0 income are excluded, and the only effect of improved economic conditions is to induce those with 0 income to enter the labor force (with a low income), then an expansion would reduce the true variance of income but increase the measured variance of income. On the other hand, bottom-coding limits our ability to observe movement at the bottom of the income distribution. So that log income is well defined without throwing out negative-, 0-, and low-income individuals, we generate a bottom code equal to the nominal wage of 500 hours of work at the real 2005 minimum wage. The top panel of table 1 shows that on average, less than 2% of each observation is affected by this bottom code, though this figure varies across cohorts. Table C.10 in the online appendix shows a variety of alternative specifications that do not rely on the bottom code (for example, 90th to 10th percentiles in lieu of variance) but yield qualitatively similar results. Results do not appear to be driven by these low outliers or the way we bottom-code them.

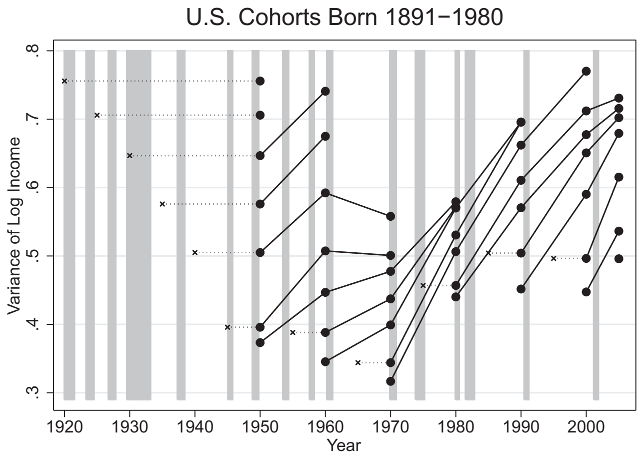
We calculate log income as $\ln\left(Y_{it}^{bottomcoded}\right)$ and excess log income as $y_{it} \equiv \ln\left(Y_{it}^{bottomcoded}\right) - g(X_{it})$, removing predictable income variation in $g(X_{it})$. y_{it} is the residual from a regression to predict log income with the following covariates: year-of-birth dummies; the interaction of calendar-year dummies, five-year age bin dummies, and race dummies; and the interaction of calendar year dummies, five-year age bin dummies, and years of education dummies.[12] The top panel of table 1 presents the variance of log income and the variance of excess log income.

We form national and state observations by examining national cohorts, based on five-year birth year bin, or state cohorts, based on (state of birth)×(five-year birth year bins, in each year. For each state, there will be seven observations (one for each possible age bin) per year and seven years of data, for a total of 49 observations. Each state-level observation comprises, on average, 4,400 individuals. Individuals in a given observation are interviewed in the same Census year and were born in the same state within the same five-year interval. We weight all analyses by the number of individuals used to construct the cross-sectional variance, as the cross-sectional variance of a larger cohort can be measured more reliably. We exclude Alaska, Hawaii, and the District of Columbia from our analysis due to cohort size and data availability issues (Owyang et al., Wall, 2005; Owyang, Rapach, & Wall, 2009).

Summary statistics on the main elements of our data are in table 1. The first panel describes state-level observations analyzed in tables 3 and 4, where a state-level observation comprises individuals born in the same five-year period in the same state observed in a Census year. The second panel describes our economic data, where the average is calculated across years for the national data and across (state) × (year) for the state data. The third panel shows the variation in lifetime economic experiences across cohorts.[13]

Figure 1 illustrates the life cycle pattern of the cross-sectional variance of log income. Each line in this figure represents one of our eighteen national birth year cohorts; the rate at which the cross-sectional variance grows with time at

FIGURE 1.—CROSS-SECTIONAL VARIANCE OF LOG INCOME



Male household heads aged 25–59 appearing in the Census between 1950 and 2000 or 2005 ACS were divided into eighteen cohorts based on five-year birth year bins. In each Census year, the cross-sectional variance of log income is computed (see the text for a discussion of zeros and bottom coding). The x markers show when the cohort was 25 to 29 years old. Gray bars indicate NBER recessions.

[10] Also, birth state economic conditions may have no impact or less impact on people who no longer reside in their birth state; such individuals will likely be affected by economic conditions in their current state that we do not consider. This may lead us to understate the magnitude of the impact of state-level conditions. See section IVD for results that attempt to adjust for this.

[11] *Inctot* is the sum of income from the following categories: wage and salary, business or farm, investment, pension, welfare, Social Security, Supplemental Security, or other. See table C.9 for the results of our analyses using wage and salary income alone or family income (the sum of *inctot* across household members in the same family.)

[12] Race categories specified in the Census and ACS are white, black, Native American, Chinese, Japanese, "other Asian," "other race," and, for 2000 and 2005 only, "two races"and "three or more races."

[13] For the eighteen national cohorts, we calculate the annual average of the economic conditions those cohorts experienced between ages 20–24 and 55–59 (adjusted for cohorts still working or for years with no stock or state GDP data). The least fortunate national cohort (and the first one in our sample, born 1891 to 1895) experienced national recession for 13 of 35 years. At the 95th percentile of state cohorts is New Mexico's cohort 15, born 1961 to 1965, who were observed in 2005 at age 40 to 44, and at that time had worked through nine years of negative growth in New Mexico's GDP in their twenty years in the labor force, for an average annual experience of 0.45.

a point in the life cycle is a measure of permanent volatility (plus the change in transitory volatility) at that point in the life cycle (equation [2]). Note that the cross-sectional variance increases monotonically (except for cohorts 5 and 6 between 1960 and 1970), at a rate of roughly 0.005 to 0.01 per year. Ceteris paribus, this corresponds to permanent income changes with a plausible annual standard deviation of 7% to 10%.

B. *Economic Conditions Data*

Except where noted, we define cumulative conditions as the sum of past economic conditions since age 20 to 24 and recent conditions as the sum over the past five years.

National economic conditions data. We adopt Storesletten et al.'s (2004) algorithm to assign NBER recessions to years.[14] As an alternative definition, we also use the fraction of months in that year classified as an NBER recession.

We collect real national GDP per person from 1890 to the present from *Historical Statistics of the U.S.* (series CA 11). We use a quadratic in real national per capita GDP growth as a continuous measure and a dummy variable for whether it is negative.

Data on stock returns and risk-free short-term interest rates (series rmgbs_*a*_) from 1926 to 2005 were obtained from Center for Research on Security Prices (CRSP). Excess log stock returns are calculated as the difference between log stock returns and interest rates.

State economic conditions data. The Bureau of Economic Analysis's Regional Economic Accounts provides GDP data for each state from 1963 (from which we use the CPI and state population to compute real GDP per capita). We include income data from 1960 in our analysis of state-level GDP variation by filling in absent GDP growth data as 0 prior to 1964. Given the (year) × (age) controls we include, we effectively ignore any cross-state variation prior to 1964.[15] We use a quadratic in real state per capita GDP growth as a continuous measure and a dummy variable for whether it is negative.

To generate state-specific annual excess stock returns, we begin by calculating the distribution of workers in each state working in each industry. CRSP stock data maps each company (in each year) to a Standard Industrial Classification (SIC) code. We hand-match these to the Census Bureau industrial classification scheme (*ind1990*), which gives the industry of each worker. The mapping yields 95 Census-CRSP-standardized industry codes (available from the authors on request); we generate industry-specific annual excess stock returns by averaging firm-specific excess stock returns, weighted by market capitalization, for each Census-CRSP-standardized industry code. The state stock return is the average of industry-specific excess stock returns in that year, weighted by the proportion of workers in each state working in each industry at the time of the most recent prior Census.[16]

We generate annual state employment changes implied by national sector-specific employment changes. We collect national employment data annually from 1939 to the present in fifteen Bureau of Labor Statistics "supersectors" (for example, Durable Goods Manufacturing, Leisure and Hospitality).[17] We use these to calculate national sector-specific annual per capita growth rates in employment. To determine the exposure of each state to national sector-specific employment shocks in each Census year, we hand-match the supersectors to the Census industrial classification (*ind1950*) and compute the fraction of workers in each sector for each state in each census year. States' year-specific exposures are imputed assuming a smooth growth rate between Census years. The state employment prediction for each state in each year is the sum of sector-specific national employment changes in each year weighted by the fraction of a state's workers in that sector in that year.

State sensitivity to national economic conditions. We measure the sensitivity of each state to national economic conditions with the following regression:

$$e_{st} = \alpha_s + \beta^{-1}_{GDP,s} e_{t-1} + \beta^{0}_{GDP,s} e_t + \beta^{+1}_{GDP,s} e_{t+1} + u_{st}. \quad (9)$$

Here, e_{st} refers to state GDP growth ("e" for economic conditions) in state s in year t (between years t and $t-1$); e_t refers to national GDP growth in year t (between years t and $t-1$). We include leads and lags because some states' economic conditions may lead or lag national ones (Hamilton & Owyang, 2009); the one-year leads and lags are chosen because we reject the hypothesis that such one-year leads or lags are jointly 0 for all states but cannot reject the hypothesis that lead or lag effects of two years or more are jointly 0 for all states. Estimates of $\beta_{GDP,s}$ for each state are presented in online appendix table B; these are generated with data from 1964 to 2005. Unsurprisingly, industrial states such as Michigan have relatively high sensitivity to national economic conditions, while rural and western states

[14] In Storesletten et al. (2004), if six or more months of the year are in an NBER peak-to-trough period, or if the year is the first year of a six- to twelve-month contraction spanning two years, the year is labeled as a recession.

[15] The BEA collects total personal income by state back to 1929. Due to our year and cohort controls, we find essentially identical results using this measure and state GDP since 1964. We report state GDP results to avoid specification errors in predicting current income moments from past income information.

[16] Due to industrial evolution over our sample period, the number of industries with stock data in a given year and employees in a given state in a given year varies from 54 to 82.

[17] The sectors are described at http://www.bls.gov/iag/tgs/iag_index_naics.htm; we use series 10, 20, 31, 32, 41, 42, 43, 44, 50, 55, 60, 65, 70, 80, and 90. Series 43, Transportation and Warehousing, and Series 44, Utilities, are missing before 1972 and 1964 respectively; we replace with data from the "supersector group" Trade, Transportation, and Utilities (Series 40).

TABLE 2.—NATIONAL ECONOMIC CONDITIONS AND CROSS-SECTIONAL VARIANCE

Time/Cohort Controls		None	Year Trend	Year Dummies	Cohort Dummies
NBER recession?	Cumulative	0.0050	0.0340	0.0275	0.0118
		(0.0098)	(0.0067)***	(0.0055)***	(0.0105)
		[0.0257]	[0.0177]**	[0.0126]***	[0.0291]
	Recent	−0.0571	0.0166	N/A	0.0157
		(0.0172)***	(0.0132)	N/A	(0.0133)
		[0.0359]**	[0.0271]	N/A	[0.0272]
Negative national growth?	Cumulative	−0.0130	0.0196	0.0132	0.0255
		(0.0090)	(0.0048)***	(0.0048)***	(0.0061)***
		[0.0265]	[0.0185]	[0.0132]	[0.0303]
	Recent	−0.0076	0.0580	N/A	0.0532
		(0.0166)	(0.0090)***	N/A	(0.0070)***
		[0.0388]	[0.0298]**	N/A	[0.0289]**
% of year in recession	Cumulative	0.0058	0.0421	0.0289	0.0217
		(0.0098)	(0.0082)***	(0.0065)***	(0.0132)
		[0.0292]	[0.0201]**	[0.0143]**	[0.0351]
	Recent	−0.1043	0.0141	N/A	0.0062
		(0.0210)***	(0.0216)	N/A	(0.0231)
		[0.0393]***	[0.0301]	N/A	[0.0312]
National GDP growth	Cumulative	−0.2164	−0.1550	−0.0798	−1.2607
		(0.1197)	(0.0680)**	(0.0477)	(0.1316)***
		[0.1859]	[0.1466]	[0.1062]	[2.0050]**
	Recent	−0.4028	0.0022	N/A	−0.5749
		(0.3398)	(0.1973)	N/A	(0.0875)***
		[0.4519]	[0.3734]	N/A	[1.9587]
Demeaned squared growth	Cumulative	0.0036	1.0073	0.7919	21.9083
		(0.4459)	(0.2754)***	(0.2016)***	(2.3701)***
		[1.3420]	[1.0464]	[0.7731]	[5.6318]***
	Recent	−1.8114	4.7992	N/A	30.8060
		(3.0642)	(1.8802)**	N/A	(3.0325)***
		[3.6218]	[3.1475]	N/A	[9.7253]***

Coefficients show the impact on the cross-sectional variance of excess log income of cumulative economic conditions, where "cumulative" refers to the cumulative sum of economic conditions from age 20–24 to five years ago, and "recent" refers to the cumulative sum of economic conditions over the past five years. Results are from least squares regression, weighted by the number of individuals represented by each observation, on 49 observations of cross-sectional income variance. Each variance is calculated on the incomes of male household heads in the labor force in one of seven age bins appearing in a U.S. Census 1% sample between 1950 and 2005. Age dummies for each age bin are included in every specification. OLS standard errors are reported in parentheses, and bootstrap standard errors (see text) are reported in brackets. Significance at **5% and ***1%.

such as Wyoming or New Mexico are less sensitive. These state-specific estimates are used to construct predicted state responses to national conditions, $\widehat{e_{st}}(e_{t-1}, e_t, e_{t+1})$.

IV. Results

A. National-Level Variation in Economic Conditions

Figure 1 shows that the cross-sectional variance generally increases over the life cycle, but that the rate of this growth is far from constant. If income volatility is higher in bad times than good, equation (2) indicates that cross-sectional variances should grow faster in periods with more recessions. NBER recessions are indicated with gray vertical bars on the figure; horizontal dotted lines show the interval over which each cohort worked but was not observed in our data.

From this figure, it is straightforward to see why regressions based on nationwide data suggest higher idiosyncratic income volatility in recessions. The cross-sectional variance of income grows slowly within a cohort between 1960 and 1970 and quickly between 1970 and 1990. Based on our model, this implies low income volatility between 1960 and 1970 and high income volatility between 1970 and 1990. The 1960–1970 interval is noteworthy both for the absence of NBER recessions (consistent with the idea that recessions increase income volatility) and for Lyndon Johnson's Great Society social programs including the war on poverty (consistent with the idea that social insurance reduces income volatility). The 1970–1990 interval is noteworthy for frequent NBER recessions (consistent with the idea that recessions increase income volatility), and rapidly rising residual wage inequality (Bound & Johnson, 1992; Katz & Murphy, 1992; Murphy & Welch, 1992; Goldin & Katz, 2001). This illustrates the difficulty of separating the effects of economic conditions from the effect of other contemporaneous policies or events.

When we include both birth cohort fixed effects and flexible age effects in a regression, we impose the restriction that the life cycle pattern in the cross-sectional variance is the same for all cohorts; cross-cohort differences are driven only by macroeconomic conditions. As a result, regression will identify countercyclical volatility if within-cohort income inequality grows faster in bad times. The slowly rising inequality in the 1960s and rapidly rising inequality in the 1970s will automatically be attributed to good and poor economic conditions during these periods, respectively. In truth, there are many other possible reasons for slowly rising inequality in the 1960s and rapidly rising inequality in in the 1970s.

Table 2 formalizes this intuition with regressions to predict the cross-sectional variance of excess log income with

TABLE 3.—STATE ECONOMIC CONDITIONS AND CROSS-SECTIONAL VARIANCE

Controls		None	Education	Education and % Black	Education, % Black, and Income
Negative state growth?	Cumulative	−0.0063	−0.0046	−0.0063	−0.0051
		(0.0019)***	(0.0019)**	(0.0019)***	(0.0020)**
		[0.0030]**	[0.0030]	[0.0031]**	[0.0031]
	Recent	−0.0012	−0.0010	−0.0011	−0.0007
		(0.0016)	(0.0016)	(0.0017)	(0.0017)
		[0.0022]	[0.0023]	[0.0023]	[0.0024]
State GDP growth	Cumulative	0.1017	0.0681	0.0902	0.0767
		(0.0227)***	(0.0244)***	(0.0248)***	(0.0250)***
		[0.0410]***	[0.0433]	[0.0445]**	[0.0443]**
	Recent	−0.0367	−0.0373	−0.0339	−0.0421
		(0.0191)	(0.0198)	(0.0199)	(0.0204)**
		[0.0179]**	[0.0180]**	[0.0182]**	[0.0189]**
Demeaned squared growth	Cumulative	−0.0270	0.0359	0.0083	−0.1809
		(0.1989)	(0.1976)	(0.1965)	(0.2055)
		[0.2083]	[0.2134]	[0.2129]	[0.2191]
	Recent	−0.2451	−0.0860	−0.1282	−0.2872
		(0.2766)	(0.2801)	(0.2783)	(0.2865)
		[0.4172]	[0.4351]	[0.4394]	[0.4438]
State employment prediction	Cumulative	0.5170	0.4996	0.4983	0.4775
		(0.1304)***	(0.1361)***	(0.1388)***	(0.1508)***
		[0.1519]***	[0.1527]***	[0.1550]***	[0.1642]***
	Recent	−0.1240	−0.1264	−0.0663	−0.1317
		(0.1180)	(0.1197)	(0.1242)	(0.1337)
		[0.1126]	[0.1134]	[0.1169]	[0.1267]

Results are the coefficients of a series of OLS regressions, weighted by the number of individuals represented in the observation, of 2,016 =(48 birth state)×(6 Census years excluding 1950)×(7 age bins) observations of cross-sectional excess log income variance on "cumulative" (age 20–24 to five years ago) and "recent" (last five years) measures of economic conditions. The final row includes 1950 and therefore uses 2,352 observations. The controls (age)×(year), (state)×(cohort), and (state) × (linear age trend) are always present. Controls for mean years of schooling, percent black, and raw log income are averaged across the seven age bins in the state in 1950 and then interacted with (age)×(year) and added in each column as indicated. OLS standard errors are reported in parentheses and bootstrap standard errors (see text) are reported in brackets. Significant at **5% and ***1%.

national economic conditions.[18] Each row tests one of the national measures described in section IIIB, where conditions over the working life of the cohort are divided into *cumulative* (from age 20 to 24 to five years ago) and *recent* (over the past five years) and show the impact of economic conditions on the variance of permanent and transitory income changes (β_σ and β_τ, respectively). All specifications include age dummies for an unrestricted age profile of volatility. Columns differ in the additional controls included: the first column excludes additional controls; the second column adds a linear trend; the third column controls flexibly for calendar-year effects; the fourth column controls flexibly for cohort effects.

Table C.1 in the online appendix shows that these results are highly sensitive to the sample and years of variation that are exploited. If we exclude variation in economic conditions from the 1966–1975 period or 1976–1985 period, the result is (insignificant but) reversed. Results also wane without the 1931–1940 birth cohort. In the baseline specification, bootstrapped standard errors are typically large enough to make point estimates insignificantly different from 0. The punch line here is that results based on nationwide variation are sensitive to identifying assumptions, samples, and error structures. These problems stem from the small amount of variation in the data. In the section IVB, we exploit the much richer variation in economic conditions available at the state level.

B. *State-Level Variation in Economic Conditions*

Table 3 presents results on the impact of state-specific economic conditions on cross-sectional income moments.[19] The first column presents results that match exactly the structure

[18] OLS standard errors are reported (in parentheses) for each regression, but errors are arguably correlated for all cohorts in a given year or for each observation of a given cohort. Therefore, we bootstrap the dispersion of estimates obtained under the null of $\beta = 0$; bootstrapped standard errors (in brackets) are obtained by repeatedly estimating the model on scrambled time series of economic data. The sample period was broken into five-year blocks (to account for short-run autocorrelation) and randomly sampled without replacement. New cumulative economic conditions for each cohort were computed for the scrambled economic history, and the regression repeated for 500 iterations. Asterisks indicate that fewer than 5% or 1% of the bootstrap coefficient estimates exceed the OLS estimate in absolute value.

[19] The bracketed rows in the first column show the standard deviation of coefficient estimates bootstrapped under the null that coefficients are 0. Rather than regressing the cross-sectional variance of a (birth state × birth year × Census year) cohort on economic conditions in the birth state, each of 500 bootstrap iterations randomly assigns (with replacement) one state's cross-sectional variance observations to another state's time series of state economic conditions. Then, for example, the cross-sectional variances for each of Idaho's seven age bins in 1950 were predicted using the cumulative economic conditions experienced by individuals at the same age in 1950 but born in Ohio. Significance was assigned if fewer than 5% or 1% of the bootstrap estimates exceeded the OLS estimate in absolute value. Due to the computational length of the bootstrap algorithm and the similarity of bootstrap standard errors to OLS standard errors, we report bootstrap standard errors only for analyses of our principal research question, the effect of economic conditions on cross-sectional variance.

presented in equation (8), with controls consistent with the restrictions in equations (6a) and (6b). Given these controls, results are identified within state cohorts over time. Subsequent columns repeat the regression in the first column with additional controls interacting (age) × (year) controls with linear measures of mean education, percentage black, or average log income in that state in 1950. This allows different patterns across states based on their educational level, race, and income. This rules out the possibility that results are driven by states of different types (for example, high and low education) having systematically different patterns in residual income inequality and also in economic performance. As in table 2, the coefficient on *cumulative* conditions measures the impact of past economic experience on the variance of permanent income shocks; the coefficient on *recent* conditions measures the effect on the variance of transitory income. (See section IIIB for the construction of the independent variables.)

Table 3 shows that past negative state growth is associated with significantly lower cross-sectional variances. When growth in state GDP or predicted state employment has been high, cross-sectional variances are significantly larger. Since the cross-sectional variance of income grows more slowly in bad times than good, permanent volatility is procyclical at the state level. Bootstrapped standard errors (in brackets) are slightly higher but do not invalidate the effect; results are robust to controls for differential age and cohort effects by state education, racial composition, and income. Table C.2 in the online appendix shows that this result is robust to excluding data from any one of the seven Census cohorts, excluding states from any of eight regions, variation in economic conditions from any five-year period, or individuals from birth cohorts in any decade. The top panel of table C.4 shows that results are robust across educational categories: among those without a high school diploma, those with a high school diploma but no further schooling, those with some college, and those with college degrees. For blacks, standard errors are much larger, so that all results are insignificant.

Note that the result found with state-level data—that volatility is higher in good times than in bad—differs in sign from what is typically assumed in macroeconomic models or found using national-level variation (in both table 3 and in Storesletten et al., 2004). There are two possible explanations for this difference. First, the difference between cross-state and nationwide results may reflect a failure of identifying assumptions. In the previous section, we showed that nationwide results are quite sensitive to choice of sample and specification. In this section, we have shown that cross-state results are quite robust to choice of sample and specification. Second, the true effect of economic conditions on income volatility may differ at the state and national levels. Poor national and good state economic conditions could be associated with high income volatility. We investigate this second possibility in the next section.

C. *Differential Impact of National-Level Economic Conditions*

The key advantage of state-based results from the previous section is that they can be identified with quite weak identifying restrictions. Results are robust to a wide variety of controls. The key disadvantage of that approach is that it may not identify the same parameter as previous nationwide results. Just because good state economic conditions are associated with high income volatility, it does not necessarily follow that good national economic conditions are as well.

In this section, we exploit the tight identifying restrictions from our cross-state identification using variation in national economic conditions. Some states experience national economic conditions more severely. If we are willing to make the assumption that cyclical variation in income volatility will be (proportionally) more pronounced in states that experience national recessions more intensely, we can identify the impact of national economic conditions on income volatility by comparing states that experience those conditions more and less intensely. This allows us to exploit national variation in economic conditions as well as the tight identifying restrictions used in our cross-state analysis. Recall from section IIIB that we generated state-specific estimates of the sensitivity of state economic conditions to national ones. We use these to construct predicted state-specific economic conditions ($\widehat{e_{st}}$) given national ones e_t.[20]

Table 4 presents results from the regression in which equation (9) is plugged into equation (8). The bracketed rows report standard errors bootstrapped in the same manner (assigning one state's cross-sectional variances to a randomly chosen other state's GDP betas) as in table 3. In states that are more sensitive to national economic conditions, NBER recessions and negative national growth (indicators) are associated with lower cross-sectional income variances. This implies that exposure to national macroeconomic fluctuations reduces idiosyncratic permanent income volatility. Our estimated coefficient in this setting is modestly larger than that in table 3; a 1 standard deviation change in a state's GDP beta has an effect twice the size of that suggested by potentially endogenous state-level data. The pattern is also apparent by examining exposure to a quadratic in national growth. The substantial and negative coefficient on the squared-deviation-from-mean term implies that income variances are lower when people are exposed to more periods when economic growth is further from its long-run average. Again, national economic fluctuations (deviations from growth trend) are associated with lower volatility.

Table 5 explores another measure of economic conditions: stock returns. We explore the impact of national stock returns (top row), the component of national stock returns likely to affect that state given the industrial composition of employment (middle row), and the relative impact of national

[20] Equation (9) was estimated using GDP growth as the measure of economic conditions (e_t); we assume that the same relationship extends to other measures of economic conditions such as NBER recessions.

TABLE 4.—PASS-THROUGH OF NATIONAL ECONOMIC CONDITIONS TO STATES AND CROSS-SECTIONAL VARIANCE

Controls		None	Education	Education and % Black	Education, % Black, and Income
β× (NBER Recession?)	Cumulative	−0.0292	−0.0270	−0.0283	−0.0270
		(0.0045)***	(0.0045)***	(0.0046)***	(0.0046)***
		[0.0067]***	[0.0067]***	[0.0070]***	[0.0071]***
	Recent	−0.0036	−0.0014	−0.0005	−0.0021
		(0.0043)	(0.0042)	(0.0042)	(0.0043)
		[0.0078]	[0.0078]	[0.0078]	[0.0078]
β× (Negative National Growth?)	Cumulative	−0.0189	−0.0158	−0.0161	−0.0160
		(0.0038)***	(0.0038)***	(0.0039)***	(0.0040)***
		[0.0057]**	[0.0057]***	[0.0060]***	[0.0061]***
	Recent	−0.0124	−0.0103	−0.0114	−0.0113
		(0.0045)***	(0.0044)**	(0.0046)**	(0.0046)**
		[0.0040]***	[0.0041]***	[0.0042]***	[0.0043]***
β× (% of Year in Recession)	Cumulative	−0.0365	−0.0321	−0.0350	−0.0330
		(0.0050)***	(0.0050)***	(0.0051)***	(0.0051)***
		[0.0088]***	[0.0089]***	[0.0092]***	[0.0093]***
	Recent	−0.0082	−0.0057	−0.0032	−0.0028
		(0.0078)	(0.0077)	(0.0077)	(0.0080)
		[0.0099]	[0.0098]	[0.0099]	[0.0102]
β× (National GDP growth)	Cumulative	−0.1133	−0.1429	−0.1935	−0.1593
		(0.0818)	(0.0813)	(0.0830)**	(0.0861)
		[0.0768]	[0.0771]**	[0.0803]**	[0.0824]**
	Recent	0.0346	0.0185	−0.0431	−0.0248
		(0.0802)	(0.0800)	(0.0814)	(0.0829)
		[0.090]	[0.0893]	[0.0915]	[0.0930]
β× (Demeaned squared growth)	Cumulative	−11.9892	−10.7351	−11.0769	−10.5451
		(1.5012)***	(1.4995)***	(1.5206)***	(1.5496)***
		[2.4095]***	[2.420]***	[2.4992]***	[2.5691]***
	Recent	−15.4757	−14.3463	−15.0460	−14.3461
		(2.0494)***	(2.0411)***	(2.0654)***	(2.0984)***
		[2.7565]***	[2.7823]***	[2.8527]***	[2.9320]***

Results are the coefficients of a series of OLS regressions, weighted by the number of individuals represented in the observation, of 2,352 =(48 birth state)×(7 Census years)×(7 age bins) observations of cross-sectional excess log income variance on cumulative (age 20–24 to five years ago) and recent (last five years) state-specific economic conditions. The economic conditions are the product of leading, lagging, and contemporaneous national conditions and a state's sensitivity to those national conditions (see the text). The controls (age)×(year), (state)×(cohort), (state) × (linear age trend) are always present. Controls for mean years of schooling, percent black, and raw log income are averaged across the seven age bins in the state in 1950 and then interacted with (age)×(year) and added in each column as indicated. OLS standard errors are reported in parentheses and bootstrap standard errors (see text) are reported in brackets. Significance at **5% and ***1%.

stock returns on states that are more sensitive to national (GDP) economic conditions. The main drawback of stock returns is that they may indicate news about expected asset returns (not real economic activity) or news about economic activity far in the future. Given this, it is unsurprising that stock-based results have large standard errors and are seldom significantly different from 0.

D. *Robustness*

So far, we have presented two strategies to examine the impact of economic conditions on income volatility: in table 3, we examined differences in state economic conditions, and in table 4, we examined states that differed in their exposure to national economic conditions. In both cases, past bad economic conditions are associated with a lower cross-sectional variance, implying that the variance of idiosyncratic income changes is lower in bad times.

Appendix C in the online supplement explores the robustness of our results in a variety of dimensions. We briefly summarize these robustness checks here. Table C.2 in the online appendix shows that this result is robust to excluding data from any one of the seven Census years, excluding states from any of eight regions, excluding variation in economic conditions from any five-year period or individuals from birth cohorts in any decade. Table C.4 shows that results are robust across educational categories: among those without a high school diploma, those with a high school diploma but no further schooling, those with some college, and those with a college degree.

Tables C.5 and C.7 show that our procyclical volatility results are driven by the procyclical volatility of highly persistent shocks. We observe a higher cross-sectional variance five or more years after good economic conditions; we do not observe a higher cross-sectional variance immediately after good economic conditions. This is consistent with the idea that highly persistent (permanent) shocks have a variance that is procyclical, while less persistent (transitory) shocks may not. As a result, our procyclical permanent volatility result is apparent only when we assume a high degree of persistence in the permanent shocks. Table C.8 shows that results are robust to allowing heterogeneous income growth rates with cyclical variance of these growth rates.

In appendix C.3 in the online supplement, we ensure that our results are not driven by our definition of income (table C.9) or bottom-coding (table C.10).

In the body of this paper, we focus on two robustness checks that are of particular interest. We show in the

TABLE 5.—STOCK RETURNS AND CROSS-SECTIONAL VARIANCE

		National Variation			
Time/Cohort Controls		None	Year Trend	Year Dummies	Cohort Dummies
ln(Stock Return)	Cumulative	−0.0497	−0.0479	−0.0391	−0.0431
		(0.0286)	(0.0170)***	(0.0141)***	(0.0261)
		[0.0698]	[0.0488]	[0.0354]	[0.0844]
	Recent	−0.0101	0.0314	N/A	0.0332
		(0.0479)	(0.0288)	N/A	(0.0277)
		[0.0925]	[0.0715]	N/A	[0.0746]
		State Variation and β× National Variation			
Controls		None	Education	Education and % Black	Education, % Black, and Income
ln(State Stock Return)	Cumulative	−0.0873	−0.0834	−0.0725	−0.0334
		(0.0511)	(0.0509)	(0.0531)	(0.0554)
		[0.0747]	[0.0747]	[0.0785]	[0.0824]
	Recent	0.0335	0.0047	0.0163	0.0291
		(0.0378)	(0.0388)	(0.0395)	(0.0410)
		[0.0453]	[0.0456]	[0.0477]	[0.0491]
β× (National Stock Return)	Cumulative	0.0097	0.0065	0.0105	0.0071
		(0.0110)	(0.0109)	(0.0113)	(0.0117)
		[0.0098]	[0.0098]	[0.0102]	[0.0104]
	Recent	−0.0227	−0.017	−0.0236	−0.0229
		(0.0130)	(0.0129)	(0.0134)	(0.0142)
		[0.0138]	[0.0139]	[0.0148]	[0.0154]

The table repeats the analyses of tables 2, 3, and 4 with measures of stock performance as the independent variable. The first panel repeats table 2 on 49 observations using excess log stock returns over the work life on the right-hand side. Age dummies are always included, and other controls are added in each column as indicated. The second panel repeats table 3 on 2,016 observations using the log of state stock returns (see the text), and the third panel repeats table 4 on 2,352 observations using the interaction of state sensitivity to national conditions (β) and excess log stock returns. The controls (age)×(year), (state)×(cohort), (state) × (linear age trend) are always present. Controls for mean years of schooling, percent black, and raw log income are averaged across the seven age bins in the state in 1950 and then interacted with (age)×(year) and added in each column as indicated. OLS standard errors are reported in parentheses and bootstrap standard errors (see text) are reported in brackets. Significant at ***1%.

next subsection that the effects of economic conditions on cross-sectional variance are qualitatively similar but modestly larger when we account for the attenuating effects of interstate migration. The following subsection shows that results are robust to a rich set of controls but are not identified within year, within state, across cohorts.

Robustness: Moving. Our results so far have been conservative in exploiting variation in birth state economic conditions; people are likely subject to economic conditions in their current state, not their birth state. Our birth state results may underestimate the true effect of economic conditions since our estimates combine the effect of a state's economic conditions on those who were born and continue to live there with the (presumably smaller) effect of a state's economic condition on those who have already left that state.

To accommodate moving explicitly, we can assume that volatility depends on both birth state (bs) and present state (ps): the dispersion of initial ability depends on birth state ($\sigma^2_{a,bsc}$), current state (but not birth state) economic conditions may affect volatility ($\beta_\varepsilon, \beta_\omega$), and birth state and current state may have year- and cohort-invariant state effects.

$$\rho = 1;\ \sigma^2_{a,bsc}\text{unrestricted};\ \sigma_{ab,sc} = \sigma^2_{b,sc} = 0, \tag{10a}$$
$$\sigma^2_{\omega,sct} = \alpha_{\omega,ct} + \alpha^{birth}_{\omega,bs} + \alpha^{present}_{\omega,ps} + \beta_\omega e_{pst}, \tag{10b}$$
$$\sigma^2_{\varepsilon,sct} = \alpha_{\varepsilon,ct} + \alpha^{birth}_{\varepsilon,bs} + \alpha^{present}_{\varepsilon,ps} + \beta_\varepsilon e_{pst}. \tag{10c}$$

We then add the aggressive assumption that those who move chose their destination state randomly, so that the expected current state effects for movers is 0 once nationwide controls are included.[21] Since only individuals who stay in their birth state are subject to the current state fixed effect and its economic conditions, we adjust these coefficients by the proportion of the cohort remaining. In this case, equations (6a) and (6b) can be modified to show the parameters for an individual born in birth state bs in cohort c now living in state ps at time t:

$$E[\alpha^{present}_{\omega,ps} + \beta_\omega e_{pst}] = \pi_{sct} \times (\alpha^{present}_{\omega,bs} + \beta_\omega e_{bst}),$$
$$E[\alpha^{present}_{\varepsilon,ps} + \beta_\varepsilon e_{pst}] = \pi_{sct} \times (\alpha^{present}_{\varepsilon,bs} + \beta_\varepsilon e_{bst}).$$

π_{sct} is the probability that someone born into state s in birth year cohort c will still live in that state by year t. One challenge is that innovations to π_{sct} may depend on e_{st}. To address this concern, we make the additional assumption that π_{sct} is slow moving and that the subsequent economic growth, stock returns, and recessions (e_{st+1}) are independent of π_{sct}; people do not leave their birth state in anticipation of future bad times

[21] This assumption is the opposite of the more conservative assumption we have made to date: that any interstate migrant moves to a state with economic conditions identical to his or her birth state. In this sense, we view our primary results as a lower bound on the phenomenon of interest and these results as an upper bound. We are also implicitly assuming that those who move are not innately different from those who stay in terms of volatility. If this assumption is violated, we are estimating the impact of economic conditions on volatility for stayers.

TABLE 6.—STATE ECONOMIC CONDITIONS AND CROSS-SECTIONAL VARIANCE: INTERSTATE MIGRATION

State Definition		Birth				Current
Sample		All	All	Stay	Move	All
π Adjustment		No	Yes	No	No	No
Negative state growth?	Cumulative	−0.0063	−0.0101	−0.0045	−0.0102	−0.0023
		(0.0019)***	(0.0035)***	(0.0025)	(0.0027)***	(0.0020)
	Recent	−0.0012	−0.0012	0.0015	−0.0054	0.0043
		(0.0016)	(0.0028)	(0.0021)	(0.0024)**	(0.0017)**
State GDP growth	Cumulative	0.1017	0.1526	0.1070	0.1324	0.0623
		(0.0227)***	(0.0421)***	(0.0294)***	(0.0344)***	(0.0246)**
	Recent	−0.0367	−0.0353	−0.0596	0.0090	−0.0988
		(0.0191)	(0.0340)	(0.0263)**	(0.0271)	(0.0207)***
DeMeaned squared growth	Cumulative	−0.0270	−0.0510	0.0565	0.0040	0.0730
		(0.1989)	(0.3997)	(0.2740)	(0.2781)	(0.2224)
	Recent	−0.2451	−0.0823	−0.1846	−0.3791	−0.3133
		(0.2766)	(0.4179)	(0.3528)	(0.4255)	(0.2875)
State employment prediction	Cumulative	0.5170	0.3594	0.4460	0.7107	0.4910
		(0.1304)***	(0.1336)***	(0.1754)**	(0.1854)***	(0.1492)***
	Recent	−0.1240	−0.1299	−0.2195	0.1499	−0.2768
		(0.1180)	(0.1169)	(0.1591)	(0.1663)	(0.1344)**
β× (NBER Recession?)	Cumulative	−0.0292	−0.0281	−0.0363	−0.0208	−0.0340
		(0.0045)***	(0.0068)***	(0.0056)***	(0.0068)***	(0.0045)***
	Recent	−0.0036	−0.0096	−0.0052	−0.0047	0.0012
		(0.0043)	(0.0062)	(0.0053)	(0.0067)	(0.0045)
β× (Negative National Growth)	Cumulative	−0.0189	−0.0249	−0.0256	−0.0111	−0.0245
		(0.0038)***	(0.0056)***	(0.0048)***	(0.0057)	(0.0039)***
	Recent	−0.0124	−0.0186	−0.0070	−0.0234	−0.0048
		(0.0045)***	(0.0063)***	(0.0058)	(0.0065)***	(0.0048)
β× (% of Year in Recession)	Cumulative	−0.0365	−0.0400	−0.0428	−0.0339	−0.0383
		(0.0050)***	(0.0077)***	(0.0063)***	(0.0076)***	(0.0051)***
	Recent	−0.0082	−0.0178	−0.0112	−0.0051	−0.0045
		(0.0078)	(0.0116)	(0.0097)	(0.0120)	(0.0082)
β× (National GDP growth)	Cumulative	−0.1133	0.1006	−0.1027	−0.1912	−0.1053
		(0.0818)	(0.1288)	(0.1078)	(0.1192)	(0.0904)
	Recent	0.0346	0.1698	0.0495	0.0099	−0.0040
		(0.0802)	(0.1187)	(0.1012)	(0.1244)	(0.0829)
β× (DeMeaned squared growth)	Cumulative	−11.9892	−15.6340	−13.8645	−11.1348	−12.7614
		(1.5012)***	(2.4571)***	(1.9456)***	(2.2481)***	(1.6007)***
	Recent	−15.4757	−19.0359	−17.0174	−15.3780	−15.5037
		(2.0494)***	(3.1640)***	(2.6304)***	(3.1171)***	(2.1814)***

The first column repeats the first columns of tables 3 and 4. The second column implements the alternative model described in section IVD by multiplying state economic conditions by the proportion of individuals in the observation still living in the birth state (at the time of the previous Census); the cumulative and recent sums of this proportion are also included. The third and fourth columns restrict the sampled individuals to those who have stayed in or, respectively, moved from their birth states. In the first four columns, an observation is the cross-sectional variance of individuals born in the same state in the same five-year period and the economic conditions in that birth state over the work life. In the fifth column, an observation is the cross-sectional variance of individuals observed in the same state in a Census year and born in the same five-year period and the economic conditions in that current state over the work life. Significant at **5% and ***1%.

but instead wait until bad times strike before departing. We implement the implied cross-sectional regression with estimates of π_{sct-k} from the most recent prior Census, obtaining the estimate from the next oldest cohort when the cohort in question was too young to be in our sample in the prior Census. Results with this moving probability adjustment (table 6, second column) are similar to but modestly larger than the baseline results (first column).

Because this adjustment implies a strong assumption (that moves are to states with economic conditions orthogonal to birth states), we consider a variety of other approaches in columns 3 to 5. Note that results are broadly similar if we consider only individuals who do not move (third column) and only individuals who do move (fourth column), as well as if we define state based on current state and not birth state (fifth column).

Robustness: Specification. Table 7 repeats table 3 but adjusts the controls and therefore the identifying restrictions. The first columns of tables 7 and 3 are the same. The second column of table 7 replaces (state)×(cohort) controls with (state)×(year) controls. This specification identifies the impact of economic conditions on cross-sectional moments when the variance of transitory shocks varies with calendar time. This specification implies two strong identifying assumptions: that the cross-sectional variance of initial income does not differ across cohorts within states and that economic conditions before age 25 have no impact on the subsequent cross-sectional variance. Identification comes from comparing the young and old within a state at a point in time, under the presumption that the old experienced past economic conditions that the young were too young to experience. When this last assumption is violated (as it would be when some members of a cohort begin work before age 25), results will be attenuated (biased toward 0). This specification yields estimates close to zero and insignificantly different from 0.

The third column exploits cross-state differences in average economic conditions. Controls for national conditions

TABLE 7.—STATE ECONOMIC CONDITIONS AND CROSS-SECTIONAL VARIANCE: ALTERNATIVE SPECIFICATIONS

		Controls			
(age)×(year)		Yes	Yes	Yes	Yes
(state)×(linear age trend)		Yes	Yes	No	No
(state)×(cohort)		Yes	No	Yes	Yes
(state)×(year)		No	Yes	No	No
Negative state growth?	Cumulative	−0.0063	0.0001	−0.0195	−0.0054
		(0.0019)***	(0.0017)	(0.0148)	(0.0015)***
	Recent	−0.0012			−0.0021
		(0.0016)			(0.0015)
State GDP growth	Cumulative	0.1017	0.0037	−0.1992	0.0648
		(0.0227)***	(0.0179)	(0.2689)	(0.0206)***
	Recent	−0.0367			−0.0325
		(0.0191)			(0.0192)
Demeaned squared growth	Cumulative	−0.0270	0.0614	−1.1283	−0.1715
		(0.1989)	(0.1367)	(1.3951)	(0.1165)
	Recent	−0.2451			−0.1401
		(0.2766)			(0.2723)
State employment prediction	Cumulative	0.5170	−0.1621	1.2391	0.2914
		(0.1304)***	(0.0494)***	(0.4341)***	(0.0551)***
	Recent	−0.1240			−0.2110
		(0.1180)			(0.1131)

Results test the sensitivity of the first column of table 3 (repeated in the first column above) to varying controls. In the first and last columns, "cumulative" refers to the sum from ages 20 to 24 to five years ago, and "recent" refers to the past five years. In the second and third columns, coefficients show the effect of cumulative economic conditions, where "cumulative" refers to the cumulative sum of economic conditions from ages 20 to 24 to the present. In the third column, the independent variable is the average economic conditions in the state over the sample period multiplied by age (see the text), and the standard errors are clustered on birth state. Standard errors are reported in parentheses. Significant at ***1%.

(age)×(year) and state-specific initial conditions (state)×(cohort) are included. Here, the independent variable is the average economic conditions for that state times the number of years of work for that cohort. The standard errors shown are clustered by state. These results effectively compare the rate of growth in the cross-sectional variance across states, comparing states with relatively good and bad average economic conditions. Unsurprisingly, average economic conditions do not differ enough across states to generate tight estimates here.

The fourth column controls for (age)×(year) and state-specific initial conditions (state)×(cohort) using the usual observation-specific measures of economic conditions instead of average economic conditions. We exploit variation both between states and over time. This specification does not include state-specific linear time trends as in table 3, making the additional assumption that permanent volatility does not vary across states (or if it does, this is not correlated with average economic conditions). Results here are consistent with those from table 3 and imply procyclical income volatility.

V. Conclusion

There is a large class of recent models in which the welfare cost of business cycles is substantial and driven by idiosyncratic income volatility (variance of income changes). For such models to be empirically relevant, either there must be more income volatility in bad times than good or more income volatility at times of greater cyclicality (deviations from trend). The first of these is confirmed, exploiting national variation with strong identifying assumptions, by Storesletten et al. (2004). Because of the small number of national recessions covered by microdata (and the resulting difficulty of separating time effects from business cycle effects), we exploit cross-state variation in economic conditions. We find no evidence of increasing income volatility in bad times or times of increased cyclicality. Instead, permanent income volatility is lower in bad state times. This is apparent by comparing states that experience growth at different times and also by comparing the impact of national economic conditions in states with high and low sensitivity to national recessions.

Although there are a variety of structural reasons to expect increased income volatility in bad times, our findings may not be too surprising. Malmendier and Nagel (2011) show that individuals who have experienced poor stock returns allocate less wealth to stocks. If risk taking in financial capital falls in bad times, risk taking in human capital may fall as well.

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