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Business Cycles and American Dreams: (DIS) Aggregate Fluctuations and Intergenerational Mobility

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BUSINESS CYCLES AND AMERICAN DREAMS: (DIS) AGGREGATE FLUCTUATIONS AND INTERGENERATIONAL MOBILITY

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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Contents

ABSTRACT

BUSINESS CYCLES AND AMERICAN DREAMS:

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In this thesis, I test my central hypothesis that aggregate economic fluctuations (business cycles) affect intergenerational economic mobility (American dreams). I exploit heterogeneity across U.S. state-level business cycles. I argue that these cycles impose countercyclical credit constraints on households that rely on credit to invest in the human capital of their children. Thus, credit constraints effectively limit the skills and expected earnings of children.

I focus on an empirical measure of absolute mobility that Chetty et al. (2017) propose: the rate of absolute income mobility, which measures the fraction of adult children who earn more than their parents earned, conditional on the parent's income rank in their income distribution. My dataset includes state-level rates of absolute income mobility for children in the birth cohorts 1950, 1960, 1970, and 1980.

My panel regressions pair state-level estimates of the rate of absolute income mobility for a particular birth cohort—the dependent variable—with state-level measures of the business cycle during the decade following the cohort year, when the child is heavily dependent on their parent. I find that average cyclical fluctuations in the economy in which children lived between the ages of 0 and 18 drive to some extent their average rate of absolute income mobility through adulthood. This relationship is statistically significant conditional on middle to relatively high percentile ranks of parent income. This may imply that middle- to high-income households rely on credit to finance investment in human capital to an extent that relatively low-income households do not.

1 Introduction

The American Dream generally requires economic mobility across generations, or what economists refer to as intergenerational economic mobility. The term intergenerational economic mobility generally describes an individual's opportunity to achieve a rank in the distribution of income that is independent of the rank the individual's parent achieved when the individual was a child. According to Chetty et al. (2014), intergenerational mobility varies substantially across the U.S. (while it has generally decreased over time); the authors identify family structure and social capital among the strongest predictors of intergenerational mobility.

Ideally, the level of an individual's income depends only on their choices and actions, independent of family income—past or present—or exogenous forces such as the neighborhood in which a child is raised (Isaacs, Sawhill, and Haskins 2008). In practice, this is not the case; exogenous forces have substantial effects on the income a child generates as an adult. The expected future outcomes for a child born to a parent whose income ranks in the top quintile of the income distribution of the parent's generation is much different than the expected future outcomes for a child born to a parent whose income ranks in the bottom quintile of the parent's income distribution. On average, a child born to a parent whose income ranks in the top (bottom) quintile of the parent's income distribution has the greatest chance to rank in the high (low) end of the income distribution as an adult (Grusky and Mitnik 2015). Economists attribute a large portion of the difference in these outcomes to intergenerational elasticity (IGE), which reflects the persistence of the parent's income rank; the greater the IGE, the greater the persistence and, thus, the less the intergenerational mobility.

In Becker and Tomes (1979), the foundational model of intergenerational economic mobility, the child's intergenerational mobility depends on family characteristics. The parent's propensity to invest in the human capital of their child and the inheritability of parental endowments drive intergenerational economic mobility. Building on this framework, Lee and Seshadri (2019) demonstrate that credit constraints increase IGE and, thus, decrease intergenerational mobility, by decreasing the amount a parent is able to invest in the human capital of their child. And, according to the authors, the timing of human-capital investments is as important as the amount invested: specifically, investments in early childhood are more productive, in terms of the child's mobility, than investments in later childhood. In effect, prevention is more successful than remediation.

My central hypothesis is that, fundamentally, aggregate economic fluctuations—business cycles—affect intergenerational mobility because imperfect capital markets impose countercyclical credit constraints on households. These constraints limit the amount a parent invests in the human capital of their child, thereby limiting the foundational skills the child acquires and the expected future income the child earns as an adult. Essentially, my working hypothesis proposes that the expected income of an adult child who was raised during a recession could be adversely affected by the parent's inability to access the credit necessary to invest fully in the human capital of the child.

The connection between business cycles and access to credit is not new. A classic case is the Great Depression, when, according to Bernanke (1983), incomplete financial markets, made fragile by an adverse aggregate shock, reduced credit intermediation to households, which most depended on bank loans. Bank loans and other forms of intermediated credit fund investments in human capital. There is strong support for (but few if any tests of) my central hypothesis, because there is ample evidence that small differences in investments in the human capital of a child early in their life matter a great deal to that child's economic mobility, in part because the foundational skills the young child acquires drive their expected future earnings

(Cunha et al. 2006, Cunha and Heckman 2007, Heckman and Mosso 2014, and Lee and Seshadri 2019).

I show that within the United States, the timing, amplitudes, and durations of short-run aggregate fluctuations—in gross state product, personal income, or unemployment, for example—instigated by macroeconomic shocks are not uniform across states. To test my central hypothesis, I exploit this state-level variation in economic performance. My panel-regression approach pairs a state-level measure of mobility for one of four child birth cohorts (1950, 1960, 1970, and 1980)—this is my dependent variable—with an average measure of state-level cyclical economic fluctuations during the decade following the birth-cohort year. For, example, for the 1950 birth cohort, one such measure of cyclical economic fluctuations is average cyclical real personal income from 1950 to 1959, when the age of a child in the 1950 birth cohort is anywhere from 0 (born in 1950) and 18 (born in 1941); this is an age range during which investments in the human capital of the child are most formative. To my knowledge, the only comprehensive examination of this general relationship between economic mobility and the business cycle is Winkelried and Torres (2019) for the case of Peru. Using a panel of national household survey data (referred to as ENAHO) from 1997 to 2016, the authors conclude economic mobility among households in poverty lags the business cycle by two years. As the economy enters recession, intergenerational mobility and entry of new families into poverty decreases; in essence, the authors conclude that the business cycle drives economic mobility.

Based on average U.S. state-level cyclical fluctuations, I conclude that aggregate fluctuations drive rates of absolute income mobility, a measure of the fraction of adult children born to a particular birth cohort who earn more real income than their parents did; this ability for an adult child to achieve a greater standard of living than their parents did is, according to Chetty et al. (2017, p.1), "one of the defining features of the American Dream." Interestingly though, the relationship is statistically significant in the cases for parental income percentile ranks, 50, 70, 80, and 90, only. Generally speaking, I interpret these results to mean cyclical fluctuations during childhood drive rates of absolute income mobility conditional on a middle or relatively high percentile rank of parent income. That these effects pertain to middle and relatively high-income households is interesting, particularly if, as I argue, the availability of credit underlies the transmission mechanism from cyclical fluctuations to economic mobility. One possible implication is that middle- to high-income households rely on credit to finance investments in human capital to an extent that relatively low-income households do not. In some sense, credit-rationing constrains only households that can access credit in the first place.

That the business cycle drives the rate of absolute income mobility implies, at the very least, the importance of macroeconomic stabilization policies in general. And, given the heterogeneity of state-level economic outcomes that I report (and exploit to test my working hypothesis), my results also imply a potential role for stabilization policies directed at individual states. For example, my results lend credence to automatic stabilization policies that direct stimulus payments to states based on state-specific economic outcomes, the sort of mechanism proposed by Claudia Sahm, for example. Moreover, my results emphasize the importance of access to loanable funds, particularly for families who rely on credit to further the investment in the human capital of their children. Broadly speaking, my results suggest that macroeconomic stabilization policies not only potentially hasten the pace of macroeconomic recoveries; such policies also potentially improve rates of absolute income mobility—a key driver of the American dream.

2 Literature Review

2.1 Measures of Intergenerational Economic Mobility

The term economic mobility describes how an individual's income changes over their lifetime relative to the distribution of incomes earned in the economy. Upward (downward) mobility describes how and to what extent an individual's income rises (falls) relative to the distribution of incomes earned in the economy. Generally speaking, the often-touted American Dream requires economic mobility across generations, or what economists refer to as intergenerational economic mobility. More precisely, intergenerational economic mobility describes an individual's opportunity to achieve a rank in the distribution of incomes earned in the economy that is independent of the rank the individual's parent achieved when the individual was a child.

Economists characterize an outcome of intergenerational mobility as either relative or absolute. Relative intergenerational economic mobility measures an individual's rank in the distribution of income relative to the rank of others in the individual's generation. Absolute intergenerational economic mobility compares the income of an adult child to the income their parents earned when the parents were the age of their adult child. Intergenerational elasticity (IGE) is a standard measure of relative mobility. IGE describes persistence across generations: the extent to which a parent's rank in the distribution of income determines their adult child's rank in the distribution of income of the child's generation (Grusky and Mitnik 2015). Chetty et al. (2014a) describe the most common empirical measure of IGE as β_Y in Equation 1, where $\ln Y_i$ is the income the adult child earns at age 30, α_Y is the average trend of incomes across generations, $\ln X_i$ is the income the parent earned at age 30, and ϵ_i is uncorrelated with $\ln X_i$.

$$\ln Y_i = \alpha_Y + \beta_Y \ln X_i + \epsilon_i \tag{1}$$

According to Equation 1, the IGE coefficient (β_Y) measures the share of the percentage change in the parent's income that is the percentage change in their child's income (Chetty et al. 2014a). Typically, this degree of persistence (β_Y) registers between 0 and 1, where 0 represents complete mobility and 1 represents complete immobility. More concretely, given $\beta_Y = 0$, a 10 percent rise (fall) in the amount of income a parent earns is not reflected in the amount of income the adult child earns. On the other hand, given $\beta_Y = 1$, a 10 percent rise (fall) in the amount of income a parent earns generates an identical 10 percent rise (fall) in the amount of income the adult child earns. The interior outcomes are most instructive: suppose, for example, $\beta_Y = 0.6$; in this case a 10 percent rise (fall) in the amount of income a parent earns drives a 6 percent rise (fall) in the amount of income the adult child earns. Thus, a relatively small IGE measure, say $\beta_Y = 0$, implies persistence across generations is low, resulting in high relative mobility because the outcome of the child is independent of their parent's outcome: the income a child earns is not influenced by the income their parents earned. Similarly, a relatively large IGE measure, say $\beta_Y = 1$, implies persistence is high, resulting in low relative mobility.

A useful way to think about the IGE measure is to think about β_Y as either Equation 2 or 3, where *cov* and *var* denote covariance and variance, respectively, and ρ_{y_i,x_i} denotes the correlation between $\ln Y_i$ and $\ln X_i$.

$$\beta_Y = \frac{cov\left(\ln Y_i, \ln X_i\right)}{var\left(\ln X_i\right)} \tag{2}$$

$$= \rho_{y_i,x_i}\frac{\sigma_{y_i}}{\sigma_{x_i}} \tag{3}$$

Equation 3 decomposes β_Y into inter- and intra-generational components of the IGE measure, which combines the *intergenerational* correlation between parental and adult-child incomes (ρ_{y_i,x_i}) and *intragenerational* deviations of incomes ($\sigma_{y_i}, \sigma_{x_i}$); the latter expression reflects income inequality at a moment in time. Changes over time of intragenerational income inequality imply $\frac{\sigma_{y_i}}{\sigma_{x_i}} \neq 1$. Thus, as Equation 3 implies, all else equal, intergenerational mobility is strongly correlated with intragenerational inequality: relatively high mobility is associated with relatively low inequality. This association is captured by the well-known Great Gatsby curve, which associates the IGE coefficient with a measure of intergenerational inequality—the Gini coefficient. The Gini coefficient represents the distribution of income within a generation. For example, a country where the amount of income earned in the economy is distributed equally registers a Gini coefficient of 0; on the other hand, a country where the amount of income earned in the economy is earned by a single individual registers a Gini coefficient of 1. Empirically speaking, the Great Gatsby curve depicts a strongly positive association between the IGE coefficient and the Gini coefficient, thus implying that intergenerational mobility is strongly (negatively) correlated with intragenerational inequality.

In order to separate the correlation between parent and adult-child incomes (ρ_{y_i,x_i}) from the influence of income inequality between generations ($\sigma_{y_i}, \sigma_{x_i}$), Chetty et al. (2014b) propose an alternative measure of relative mobility they call the rank-rank slope. This measure correlates the adult child's rank in their income distribution with that of their parent's. The authors first create percentile bins; for each generation, the authors divide the range of incomes earned in the economy into 100 separate bins. Based on the amount of income an individual earns, the authors assign each individual a rank between 1 and 100. Thus, the rank-rank slope measure, β_R in Equation 4, isolates the *intergenerational* correlation between parental and adult-child outcomes; as such, the measure is independent of changes in *intragenerational* income inequality. In Equation 4, R_i is the percentile rank of adult-child i's income in their generation's distribution of income, P_i is the percentile rank of parent i's income in their generation's distribution of income, and υ_i is uncorrelated with P_i.

$$R_i = \alpha_R + \beta_R P_i + \upsilon_i \tag{4}$$

Thus, percentile ranks are distributed uniformly by construction due to the range of ranks (1 to 100) being the same for every generation; the standard deviation of adult child ranks is equal to the standard deviation of parent ranks ($\frac{\sigma_{R_i}}{\sigma_{P_i}} = 1$; see Equation 3). Therefore, β_R measures simply the correlation between an adult child's income rank in their income distribution and her parent's income rank in the parent's income distribution ($\beta_R = \rho_{R,P}$). In this way, this so-called rank-rank slope is independent of changes over time in *intragenerational* income inequality.

Moreover, because α_R is the expected income rank of adult-child i's income conditional on parent i's income rank equal to zero ($P_i = 0$), β_R captures the difference between the expected income ranks of children born to parents at the top versus the bottom of the income distribution: $\beta_R \times 100 = R_i^{100} - \alpha_R$ (Chetty et al. 2014b). Again, the higher the slope coefficient, the lower the relative mobility. In any case, empirically speaking, increases in income inequality over time tend not to decrease intergenerational mobility, because much of the increase occurs at the top one percent of the income distribution, where the Gini coefficient and economic mobility are positively correlated (Chetty et al. 2014b).

A disadvantage to using the IGE measure to gauge improvements in mobility is that, unlike an absolute-mobility measure, a relative-mobility measure does not distinguish between improving and worsening income outcomes: increased mobility could be achieved by worsening outcomes of the rich, for example, in which case, more mobility is not welfare improving (Chetty et al. 2014b). A common measure of absolute mobility, which Chetty et al. (2014b) call absolute upward mobility at percentile rank p, characterizes the adult-child i's income rank in their income distribution conditional on parent i's income rank in their income distribution equal to a given percentile rank, p; the authors focus on parents at the 25th percentile of the income distribution, or so-called *upward absolute mobility at percentile* 25. In the context of Equation 4, given estimates of α_R and β_R, the absolute mobility at, say, the twenty-fifth percentile, $\bar{r}^{25}$, is expressed as, $\bar{r}^{25} = \alpha_R + \beta_R \times 25$.

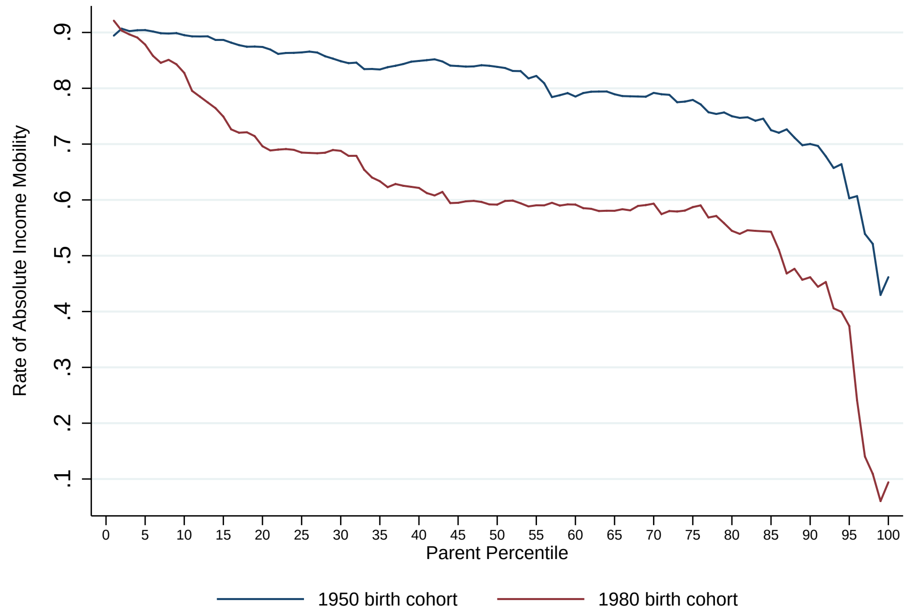
Finally, according to Chetty et al. (2017), one popular way to capture the American Dream is through the rate of absolute income mobility, a measure of the fraction of adult children born to a particular birth cohort who earn more real income at age 30 than their parents did at age 30. For example, a rate of absolute income mobility measure of 0.6 implies that 60 percent of children generated (at age 30) more income than their parents generated (at age 30). As the absolute income mobility rate increases (decreases), more (less) children earn a level of income greater than their parents earned. Equation 5 specifies the rate of absolute income mobility for children of birth-cohort c who are born to a parent in percentile $\widetilde{p}$ of the income distribution; y^k_{ic} denotes the income of child (or *kid*) i in birth cohort c, y^p_{ic} denotes the income of child i's parent, and N_c denotes the number of children in the cohort.

$$A_{\widetilde{p},c} = \frac{1}{N_c} \sum_i 1\{y^k_{ic} \geq y^p_{ic}\} \tag{5}$$

For example, in Figure 1, I illustrate the rate of absolute income mobility for South Dakota for the children in the 1950 and 1980 birth cohorts conditional on the parental income percentile rank (measured along the x-axis). The rate of absolute income mobility trends downward as the parental income percentile rank increases. And, in general, the fraction of adult children who earn more income than their parents earned has decreased over time (for South Dakota and the United States more generally); the rate for the 1980s birth cohort is lower than that of the 1950 birth cohort at almost every parental income percentile rank.

According to Figure 1, a child born in the 1950 birth cohort to a parent in the

Figure 1: Rates of Absolute Income Mobility Conditional on Parental Percentile Rank: South Dakota



25th percentile of the parent's income distribution has a rate of absolute income mobility of about 0.86: this is to say, 86 percent of South Dakota children in the 1950 birth cohort generated (at age 30) more income than their parents generated (at age 30). The comparable figure for the 1980 birth cohort is about 0.68, or roughly twenty percent less than the rate associated with the 1950 birth cohort. Meanwhile, a child born in the 1950 birth cohort to a parent in the 90th percentile has a rate of absolute income mobility of about 0.70. Thus, the percentage of children who earn more income than their parent once did decreases as the parental income percentile rank increases from 1 to 100. In any case, a change in the rate of absolute income mobility does not necessarily correspond to a change in the child's rank within their generation's income distribution. Although a child's income may increase relative to their parent's income, the child's rank in their generation's income distribution may not change—increase or otherwise—given that other children of the same generation may also earn more income than their parents earned (Chetty et al. 2017). To test my central hypothesis, $A_{\tilde{p},c}$, the rate of absolute income mobility (illustrated for South

Dakota in Figure 1), is the ideal measure of intergenerational mobility. Thus, this measure is my dependent variable in all of my forthcoming regression analyses.

2.2 Patterns of Intergenerational Economic Mobility

All measures of economic mobility, whether relative or absolute in nature, vary between nations. Typically, the IGE for developed countries is relatively low, indicating that intergenerational mobility in developed countries is relatively high; so, in terms of intergenerational mobility, developed countries fair relatively well compared to other countries. Though intergenerational economic mobility in the United States ranks low compared to other developed countries. For example, the unconditional IGE in the U.S. is about 0.5; as such, the U.S. exhibits some of the lowest mobility of developed countries; in contrast, the unconditional IGE in Canada is about 0.25 (Berger 2018 and Solon 2004). Therefore, compared Canada, in the United States, the outcomes of a parent affect the outcomes of her child twice as strongly. A parent in the United States whose income falls by 10 percent expects her child's income to fall by 5 percent; whereas a parent in Canada whose income falls by 10 percent expects her child's income to fall by 2.5 percent. Meanwhile, some developed countries have an IGE measure of less than 0.2; examples include Denmark, Finland, and Norway (Corak 2013).

In order to explain the variation of intergenerational mobility across countries, Solon (2004) models a steady-state IGE, through optimizing behavior of families, in terms of inheritability of income-related traits, the marginal product of parent's investments in the human capital of children, the earnings return to the stock of human capital, and the level of public investment in human capital. The author does this by modeling changes in IGE across countries after a shock to either the return to human capital investment or the level of public investment. According to the author, a country with low (high) intergenerational mobility, and, so, high (low) IGE, exhibits strong (weak) inheritability, high (low) marginal product of investment, high (low) returns to the stock of human capital, or a less (more) progressive system of public investment, all of which increase (decrease) intergenerational income persistence.

Across countries, differences in intergenerational mobility is correlated with inequality. This correlation exemplifies the Great Gatsby curve, the association between the IGE coefficient and the Gini coefficient. Corak (2013) illustrates the curve for several countries, for which the association is strongly positive: the more inequality of economic outcomes, the greater the IGE (which translates to lower mobility). Within the United States, increases in income inequality across time do not decrease intergenerational mobility in the ways economists generally expect. This is likely because, in the United States, increases in inequality typically happen in the top 1 percent of the income distribution (Chetty et al. 2014a). According to Chetty et al. (2014b), the relationship between the Gini coefficient for the bottom 99 percent (calculated by taking out the top 1 percent of wage earners) and upward economic mobility is negative. For the bottom 99 percent, an increase in income inequality of one percentage point causes upward economic mobility to decrease by approximately 0.63 percentage points. However, for the top 1 percent, an increase in income inequality of one percentage point causes upward economic mobility to *increase* by 0.1 percentage points. Thus, the top 1 percent of the income distribution distorts the Great Gatsby effects that economists generally expect.

The extent of income inequality in the United States between the top 1 percent and the bottom 99 percent of income earners emphasizes the vastly different outcomes across the parent's income distribution. In the United States, relative and absolute intergenerational economic mobility vary greatly conditional on the rank of the parent in their income distribution. This conditional variation leads to very different standards of living for children born to families at opposite ends of percentile ranks in the income distribution. Based on tax and other administrative data, Grusky and Mitnik (2015) conclude that children born to parents who rank in the top percentiles experience outcomes that are much different than the outcomes experienced by children born to parents who rank in the bottom percentiles. Unconditional on where a parent ranks in her generation's income distribution, the IGE registers about 0.5; thus, a one percent increase in a parent's income increases their child's income (earned as an adult) by about 0.5 percent. However, a one percent increase in the income of a parent whose income ranks between the 50th and 90th percentiles of their generation's income distribution yields about a 0.65 percent increase in the income of their child; the comparable IGE for a parent whose income ranks between the 10th and 50th percentiles of their generation's income distribution is about 0.4 (Grusky and Mitnik 2015). Therefore, a given increase in the amount of income earned by parents is most beneficial to the children whose parents rank relatively high in their income distribution.

Differences of the IGE measure, conditional on the parental percentile rank, are also present in other countries. The relationship between the earnings of fathers and sons in select Nordic countries—namely, Denmark, Norway, and Finland—conditional on the income percentile rank of the parent differs greatly from the corresponding relationships for the United States and the United Kingdom. Bratsberg et al. (2007) regress the log incomes of sons on the log incomes of fathers. The resulting relationship is strongly linear based on data for the UK and US.; however, the resulting relationship is convex based on data for these Nordic countries. In order to better understand the IGE within the Nordic countries, the authors report IGEs for these countries and the United States for the 10th, 50th, and 90th parental percentile ranks.

For Denmark, the authors report an IGE measure of 0.063 at the 10th percentile and 0.312 at the 90th percentile, suggesting a low-income-earning father does not adversely affect his child's earning potential, while a high-income-earning father affects his child's earning potential to some degree. For the United States, on the other hand, the authors report an IGE of 0.489 at the 10th percentile and 0.646 at the 90th percentile, suggesting a low-income-earning father has a relatively large (adverse) effect on his child's earning potential. The authors attribute these differences in intergenerational mobility to difference in educational policy. Generally, Nordic countries redistribute more resources to poor community schools in order to help every child reach a minimum learning standard across the entire country and offset the educational disadvantages experienced by students whose parents rank relatively low in the income distribution (Bratsberg et al. 2007).

Chetty et al. (2017) demonstrate the variation of absolute mobility conditional on the parent's rank in their income distribution using a transition matrix; the authors focus on the United States. The authors divide the income of the 1984 birth cohort, the most recent cohort at the time the study was published, into percentile bins and find the percentage chance a child falls into a specific percentile rank conditional on the percentile rank of the parent. A child born to a parent who ranks relatively high in their income distribution has a relatively good chance to rank high (as an adult child) in their income distribution. Specifically, a child born to a parent who ranks in the 10th percentile has a 28 percent chance of reaching a percentile rank of 50 or higher; a child born to a parent in the 50th percentile has a 52 percent chance of reaching a percentile rank of 50 or higher; and a child born to a parent in the 90th percentile has a 70 percent chance of reaching a percentile rank of 50 or higher. Clearly, the rank of a parent can create large differences in outcomes for children. By simulating a more equal distribution of income growth, the authors significantly reduce the decline in intergenerational mobility throughout the United States, suggesting that economic growth must be shared more equally across the income distribution in order to raise absolute mobility.

On average, economic growth necessarily raises household income and, thus, upward mobility measured as the percentage of children whose level of family income is higher than that of her parent's (Issacs, Sawhill, and Haskins 2008). This type of measure of intergenerational mobility—the rate of absolute income mobility specified by Equation 5 is one such example—uses actual, inflation-adjusted dollar amounts, which, generally speaking, economic growth strongly affects. Economic growth is often thought of as a rising tide; as the water level, or economic activity in this case, increases, it lifts all boats, or personal incomes in this case, equally. Equally distributed economic growth would increase the incomes of all adult children, independent of parental percentile rank; thus, equally distributed economic growth would not change the rank of each child in their income distribution. Nevertheless, economic growth would increase the rate of absolute upward mobility for all children, because each would earn more than their parents earned.

Practically speaking, in the United States, the positive effect that economic growth has on upward mobility has decreased because the growth is increasingly shared unequally. To show the difference in income growth across the income distribution, Isaacs, Sawhill, and Haskins (2008) divide the income distribution into quintiles and measure the median income of each quintile for both the parent's generation, averaged between 1967 and 1971, and the children's generation, averaged between 1995 and 2002. In recent years, households that earn incomes that rank in the upper fifth of the income distribution have experienced the majority of household-income growth. Specifically, the median income of the top quintile increased by 52 percent from the parents' generation to the children's generation, while the median income of the bottom quintile increased by only 18 percent (Isaacs, Sawhill, and Haskins 2008). In this case, a child born to a parent who ranks in the top quintile will experience a stronger tide, raising their income more than the income of a child born to a parent who ranks in the bottom quintile. This finding is similar to that of the Congressional Budget Office, which reports a 69 percent increase in after-tax income for the top quintile compared to a 6 percent increase in after-tax income for the bottom quintile.

A child born to a parent in the bottom quintile experiences less income growth over the child's lifetime than a child born to a parent in the top quintile experiences.

Regardless of the variation of intergenerational mobility across the income distribution, IGE has increased—and, correspondingly, relative intergenerational economic mobility has decreased—over time. Aaronson and Mazumder (2008) demonstrate this pattern for the United States using decennial census data to create synthetic father-son pairs. The authors find that the IGE increased sharply between 1980, when the IGE registered 0.31, and 2000, when the IGE registered 0.57. This rather large increase in IGE after 1980 translates into greater intergenerational earnings persistence across families; the effects from the change in the income a parent earns affects multiple future generations and it takes longer for each generation to regress towards the average income of each generation's income distribution (Aaronson and Mazumder 2008). An adult child in 1980 (from the 1950 birth cohort) experiences 30 percent of his father's deviation from the mean income of his income distribution; whereas an adult child in 2000 (from the 1970 birth cohort) experiences half of his father's deviation from the mean income of his income distribution. More concretely, if a father's income rose (fell) by 10 percent, his child's expected income at age 30 in 1980 rose (fell) by 3.1 percent; the corresponding rise (fall) in a child's expected income at age 30 in 2000 was 5.7 percent. Therefore, intergenerational persistence has increased over time, creating less economically mobile circumstances.

Absolute economic mobility has decreased over time as well. Based on de-identified tax records, Chetty et al. (2017) report that the rate of absolute income mobility (expressed by Equation 5) has trended downward, implying that the fraction of children whose level of income is higher than that of her parent's has decreased, independent of parental percentile rank; put differently, the sort of curve illustrated in Figure 1 has generally shifted downward over time across the United States. The decline in the rate of absolute income mobility is evident across various subgroups including, for example, parental percentile rank, gender, and state. The most drastic fall has occurred for children born into families whose income ranks in the middle of the income distribution. In the case of gender, the percentage of daughters earning more than their fathers fell from 43 percent in 1940 to 26 percent in 1984; meanwhile, the percentage of sons earning more than their fathers fell from 95 percent in 1940 to 41 percent in 1984. Though, to be sure, the number of daughters who worked in 1940 was lower than in 1984, and this pattern makes the fall in the rate of absolute mobility for daughters larger than otherwise. In the case of states, Michigan experienced the largest fall in the percentage of children earning more than their parents, falling by 48 percent between 1940 and 1980; the experience in Michigan is followed closely by a 45-percent fall in Illinois, Indiana, and Ohio. The smallest fall of 35 percent occurred in Massachusetts, New York, and Montana. Based on a counterfactual simulation in which individuals in each income rank share economic growth (between 1940 and 1980) equally, the authors estimate a national-level rate of absolute income mobility of 62 percent, which is 12 percent more than the actual value. Therefore, the authors attribute much of this widespread decline in absolute mobility to the unequal distribution of economic growth (Chetty et al. 2017).

Intergenerational mobility varies across regions of the United States at any point in time as well. For example, some states within the nation consistently experience lower mobility than other states (Berger 2018). States within the Great Plains region consistently experience the highest intergenerational mobility, while states in the Southeast region consistently experience the lowest intergenerational mobility (Chetty et al. 2014b). Indeed, this interstate variability is quite large: intergenerational mobilities in states such as Utah, Idaho, and Wyoming are as high as that in Canada and other countries in which mobility is high; meanwhile, mobilities in states such as Mississippi, Louisiana, and Alabama are as low as that in developing countries where mobilities are typically quite low (Chetty et al. 2014b).

Moreover, the variation in intergenerational mobility occurs *intrastate*. Chetty et al. (2014b) divide states into commuting zones, which typically include multiple counties and are determined by population. For example, the state of Michigan includes 83 counties, 533 cities, and 18 commuting zones. The authors find intergenerational mobility varies across commuting zones. For example, mobility (measured as IGE) in Mississippi varies between 0.51 in the Yazoo City, MS commuting zone and 0.34 in the Gulfport, MS commuting zone; likewise, mobility varies between 0.46 in the Devils Lake, ND commuting zone and 0.07 in the Linton, ND commuting zone. According to Chetty et al. (2014b) and Sharkey and Torrats-Espinosa (2017), race, segregation, crime, income levels, inequality, school quality, social capital, and family structure explain much of this variability. For example, all else equal, a child who lives in a neighborhood when it experiences a fall in violent crime achieves (as an adult) an expected income rank that is higher than otherwise (Sharkey and Torrats-Espinosa 2017); these results are based on FBI Uniform Crime Reports that specify the areas and severities of crimes throughout the country. According to the authors, the frequency and severity of violent crime in a county decrease the average mobility of children raised there, because increases in violent crimes increase high-school dropout rates (Sharkey and Torrats-Espinosa 2017). Meanwhile, according to Kotera and Seshadri (2017), who model the accumulation of human capital of a child as a function of public spending on schools and private spending on children by parents, when public school spending is primarily distributed toward districts whose residents rank relatively high in the income distribution, intergenerational mobility in that area is low (Kotera and Seshadri 2017).

Finally, an important and timely variable that explains some of the variation in intergenerational mobility across regions of the United States is the historical pattern of racial segregation. Andrews et al. (2017) determine that racial segregation in 1880 is negatively related to mobility for adult children, age 30, during the 2010s across the states. The authors specify the relationship between past racial segregation, measured as the rate of each race of the head of households within neighborhoods, and economic mobility of children who become wage-earning adults in the 2010s. IPUMS provides information on neighborhood segregation gathered from the US Census. Intergenerational mobility in commuting zones that experienced a higher pattern of racial segregation in the past is consistently lower; specifically, a 1 percent increase in neighborhood segregation in 1880 results in a 0.06 increase in IGE and, thus, a decrease in intergenerational mobility (Andrews et al. 2017).

2.3 Models of Intergenerational Economic Mobility

The patterns of economic mobility across countries, regions, and time, sparks an intriguing question of how precisely the income that parents earn influences the income that their children earn. Generally, economists attribute this intergenerational relationship to the amount a parent invests in the human capital of their child. Becker and Tomes (1979) model the transmission of income inequality across multiple generations of a single family. In this model, the authors demonstrate how the utility of each generation depends on their own consumption as well as the income of the next generation. Parents increase the income of their children (and, therefore, the utility of the parents) by investing in their children's human capital or endowing their children with income-earning traits, including culture for example; market luck and endowment luck play (non-systematic) roles as well. Meanwhile, capital markets function perfectly.

Becker and Tomes (1986) expand on this utility maximizing model to understand the role capital markets play in driving intergenerational mobility. In perfect capital markets, families from every income level are able to maximize their investment in the human capital of their children through borrowing and without decreasing their own consumption. The amount a parent borrows in order to maximize their investment depends on their income. A parent with less disposable income borrows more than a parent with more disposable income. Therefore, the former passes on a larger amount of debt to their child than does the latter; this additional debt burden decreases the future economic welfare of children from families lower in the income distribution. In imperfect capital markets, parents at the bottom of the income distribution must decide between consumption and investment. Binding credit constraints raise the cost of borrowing and lower the parent's investment in human capital and, thus, the adult earnings of her child, effectively reducing intergenerational mobility. I return to this model in Section 3.

At what stage of the child's life the parent invests in the human capital of the child matters. Cunha and Heckman (2007) model self productivity, or how skills produced at a young age compound over time. When a parent invests in the human capital of her child early in the child's life, the investment builds a cognitive foundation on which future human capital investments can take root. In this model, if the parent under invests early on, the child's skill set is forever less than it would have been otherwise. In order to demonstrate this compounding nature of investments in the creation of skills, Cunha et al. (2006) model human capital accumulation as the result of a continuous stream of investments from parent to child and the marginal productivity of each investment, or skills multiplier. Based on this model, the authors demonstrate the importance of timing: the ratio of early to late-stage human-capital investments is positively related to the skills multiplier (Cunha et al. 2006). Because relatively young children tend to have relatively young parents, and because relatively young parents often face life-cycle borrowing constraints that prevent them from investing in the human capital of their child, these borrowing constraints could significantly affect a child's ability to earn relatively high income as an adult.

Finally, if borrowing constraints bind, parental skill may matter as well. According to Heckman and Mosso (2014), if the parent's ability to borrow in order to invest early in the life of their child depends on the parent's skill set, a relatively highly skilled parent is able to borrow relatively more and therefore invest relatively more in the human capital of their child. Thus, the skill set of the parent produces intergenerational effects, because a parent with a relatively large skill set effectively produces a child with a relatively large skill set; and the ability to earn income is positively related to size of an income-earner's skill set.

To be sure, this often-modeled relationship between borrowing constraints and intergenerational mobility is potentially very strong. Lee and Seshadri (2019) model human capital investment over various stages of childhood while accounting for the stock of skills a child collects throughout his life. The authors demonstrate that small differences in investment in the human capital of children early in life matter a great deal. The authors attribute about one third of IGE to younger parents, who tend to experience borrowing constraints that are tighter than those that older parents experience. According to the authors, relaxing the life cycle budget constraint—loosening the borrowing constraints of young parents—reduces intergenerational persistence and thus, increases intergenerational mobility. As the borrowing constraint on young parents loosens, they are able to invest more in the human capital of their child, decoupling the link between the amount of income the parent earns from the amount of income the adult child earns. The authors also model government intervention and education subsidies directed to the earliest period of children's lives. The redirection of subsides in this way decreases the IGE significantly, from 0.3 to 0.1. Education subsidies in the earliest period of childhood assists young parents who face borrowing constraints, causing positive long run outcomes; the average human capital stock is higher, leading to higher earnings for the economy as a whole (Lee and Seshadri 2019).

3 The Models

In Section 3.1, I link intergenerational elasticity to credit constraints in order to establish the channel through which tightening credit constraints affect the future economic welfare of children. The model illustrates how the amount a parent invests in the human capital of their child determines their future economic success, and so too their intergenerational mobility. Specifically, tightening credit constraints decrease the amount a parent is able to invest in the human capital of their child, resulting in a decrease in the expected future economic welfare of the child. In Section 3.2, I link aggregate fluctuations to credit constraints to demonstrate in what way aggregate shocks cause the supply of credit to decrease. Using these models, I show that through credit channels, aggregate fluctuations affect the amount a parent invests in the human capital of their child; and, as such, aggregate fluctuations have implications for intergenerational economic mobility.

3.1 Becker and Tomes: Intergenerational Elasticity and Credit Constraints

According to the extant literature, the income an adult child earns depends on the income their parents earned. A canonical class of models of mobility associate it with intergenerational investments in human capital, inheritances of family endowments, and market and endowed luck, neither of which the parent or child determines. In order to model precisely a transmission of income from a parent to a child, and the role that imperfect credit markets play in this transmission process, I begin with Becker and Tomes (1979). In this model of multiple generations of a single family, the utility of each generation depends on their consumption and the income of the next generation. The model assumes perfect capital markets—an assumption I relax going forward—and, thus, borrowing constraints do not bind.

Becker and Tomes (1979) propose a utility maximizing model in which parents maximize their children's future economic welfare, or adult net earnings—the difference between all inflows of income and outflows of debt service. In this model, parental earnings are potentially transferred to children in two ways: endowments in the form of risk-free assets and expenditures in investments in the human capital of the child. The parent's utility function at time t, U_t, is specified in Equation 6, where Z_t is the consumption of the parent in period t and I_{t+1} is the (aggregate) wealth of the child.

$$U_t = U_t\left(Z_t, I_{t+1}\right) \tag{6}$$

The parent maximizes Equation 6 subject to the budget constraint specified in Equation 7, where r_t is the rate of return (per generation) on investment in children, e_{t+1} is the realization (in period $t+1$) of the endowment, u_{t+1} is the realization of market luck, and w_{t+1} is the value to children of each unit of the endowment and market luck; following Becker and Tomes (1979), I denote the right-hand side of Equation 7 as S_t.

$$Z_t + \frac{I_{t+1}}{1+r_t} = \underbrace{I_t + \frac{w_{t+1}e_{t+1}}{1+r_t} + \frac{w_{t+1}u_{t+1}}{1+r_t}}_{S_t} \tag{7}$$

The parent satisfies first-order conditions, setting the marginal rate of substitution—the rate at which the parent can decrease their consumption in order to increase investment without decreasing their utility—equal to the (inter-temporal) gross rate of return on investment in children; doing so yields Equation 8.

$$\frac{\partial U_t}{\partial Z_t} / \frac{\partial U_t}{\partial I_{t+1}} = 1 + r_t \tag{8}$$

Becker and Tomes (1979) assume Equation 6 is homothetic and, thus, homogenous of degree 1: utility depends only on the ratio of two goods. I assume the monotonic transformation holds in order to solve the problem analytically. Accordingly, I assume Equation 6 takes the constant relative risk aversion, CRRA, form of Equation 9, where θ is the coefficient of relative risk aversion and γ measures the parent's relative preference for the wealth of the child (I_{t+1}).

$$U_t = \frac{Z_t^{1-\theta}}{1-\theta} + \gamma \frac{I_{t+1}^{1-\theta}}{1-\theta} \tag{9}$$

I solve the model under certainty. Thus, I assume the parent correctly anticipates, in period t, the realizations of the endowment (e_{t+1}) and market luck (u_{t+1}); doing so yields the following expressions for I_{t+1} and Z_t, respectively.

$$\frac{I_{t+1}}{1+r_t} = \underbrace{\frac{\gamma^{\frac{1}{\theta}} \left(1+r_t\right)^{\frac{1-\theta}{\theta}}}{1+\gamma^{\frac{1}{\theta}} \left(1+r_t\right)^{\frac{1-\theta}{\theta}}}}_{\alpha(\gamma, 1+r_t)} S_t \tag{10}$$

$$Z_t = \left(1-\alpha\right) S_t \tag{11}$$

In Equation 10, the slope parameter—based in this case on CRRA utility (Equation 9)—is the specific functional form of the term, $\alpha\left(\gamma, 1+r_t\right)$, to which Becker and Tomes (1979) refer.[1] Not surprisingly, investment in children is increasing in the relative preference for the wealth of children: $\frac{\partial\alpha(\gamma,1+r_t)}{\partial\gamma} > 0$; whereas the sign of $\frac{\partial\alpha(\gamma,1+r_t)}{\partial r_t}$ depends on the magnitude of θ relative to 1: if $\theta < 1$, the substitution effect dominates and $\frac{\partial\alpha(\gamma,1+r_t)}{\partial r_t} > 1$; and if $\theta > 1$, the income effect dominates and $\frac{\partial\alpha(\gamma,1+r_t)}{\partial r_t} < 1$.

[1] See, for example, Equation 8 on page 1157 of Becker and Tomes (1979).

Substituting in Equation 10 for the definition of S_t specified in Equation 7 yields Equation 12, where, following Becker and Tomes (1979), I denote $\alpha\,(1+r_t)$ as β_t—the parent's propensity to invest in her children.

$$I_{t+1} = \underbrace{\alpha\,(1+r_t)}_{\beta_t}\,I_t + \alpha w_{t+1} e_{t+1} + \alpha w_{t+1} u_{t+1} \tag{12}$$

Therefore, the aggregate wealth of children, I_{t+1}, is not only dependent on the inclination of their parents to invest, β_t, and the aggregate wealth of their parent, I_t, but also on the realization of the endowment, e_{t+1}. Becker and Tomes (1979) propose the (child's) endowment-generating equation specified in Equation 13, where h is the share of the parent's endowment, e_t, that the child inherits from the parent, $\bar{e}_t$ is the average endowment of generation t, f is the (generational) growth rate of $\bar{e}_t$, and υ_{t+1} is the difference between the actual and the expected endowment.

$$e_{t+1} = (1-h+f)\,\bar{e}_t + h e_t + \upsilon_{t+1} \tag{13}$$

According to Becker and Tomes (1979, 1159), the term $(1-h+f)\,\bar{e}_t$ "is a simple way of incorporating the influence of the 'culture' or 'social capital' of other families." The influence from these additional sources is relevant to understanding how I_{t+1} is formed. Combining Equations 12 and 13 by eliminating e_{t+1} yields Equation 14.

$$I_{t+1} = \alpha w_{t+1}\,(1-h+f)\,\bar{e}_t + \beta_t I_t + \alpha h w_{t+1} e_t + \alpha w_{t+1} \upsilon_{t+1} + \alpha w_{t+1} u_{t+1} \tag{14}$$

Based on the assumption that the parameters in the model and the average endowment ($\bar{e}_t$) are stationary (and, so, the statistical properties such as mean and the variance are constant over time), Becker and Tomes (1979) set $(r_t, w_t) = (1,1)$ and

$f = 0$ in Equation 14; doing so yields Equation 15, which specifies the income of the child of generation i, where $a = (1 - h)\,\bar{e}$.

$$I^i_{t+1} = \alpha a + \beta I^i_t + \alpha h e^i_t + \alpha v^i_{t+1} + \alpha u^i_{t+1} \tag{15}$$

Finally, combining Equations 12 and 15 by eliminating endowments, e, yields, by lagging Equation 12 by one period, Equation 16, where $u^{*i}_{t+i} = u^i_{t+1} - h u^i_t + v^i_{t+1}$.

$$I^i_{t+1} = \alpha \bar{e}\,(1 - h) + (\beta + h)\, I^i_t - \beta h I^i_{t-1} + \alpha u^{*i}_{t+i} \tag{16}$$

Equation 16 depicts how the income of a parent functionally affects the income of an adult child. To learn how these parameters, most notably β and h, affect income, I use the model to specify the IGE. In large samples, this IGE measure obtains by regressing the log of child income on the log of parent income (see, for example, Equation 1); in the probability limit, the resulting regression slope coefficient measures the IGE, as specified in Equation 17.

$$IGE \xrightarrow{p} \frac{Cov\,(\log I_t, \log I_{t+1})}{Var\,(\log I_t)} \tag{17}$$

Writing Equation 17 as Equation 18 and assuming a stationary (long-run) equilibrium, I take the covariance of both sides of Equation 16 with I^i_t and I set $\frac{I_t}{I_{t+1}} = 1$ (in Equation 18); doing so yields Equation 19, where $b_{u_t, I_t} = \frac{Cov(u_t, I_t)}{Var(u_t)} > 0$.

$$IGE \xrightarrow{p} \frac{Cov\,(I_t, I_{t+1})}{Var\,(I_t)} \frac{I_t}{I_{t+1}} \tag{18}$$

$$\xrightarrow{p} \frac{\beta + h\,(1 - \alpha b_{u_t, I_t})}{1 + \beta h} \tag{19}$$

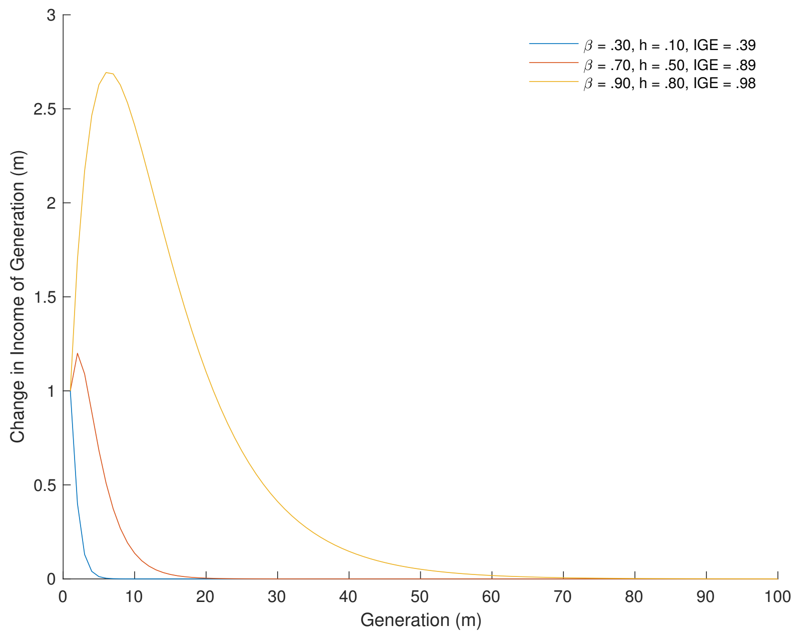
Thus, as $\beta, h \rightarrow 0$ and, thus, as the parent's propensity to invest in her child (β) and the share of the parent's endowment passed to her child (h) approach zero (one), IGE approaches zero (one): intergenerational mobility increases (decreases). Therefore, when the parent is less inclined to invest a share of their income in the human capital of their child and when the share of endowments passed from parent to child is low, intergenerational persistence is low and the income of a child becomes less dependent on the income of their parent—thus, intergenerational mobility is high.

Additionally, a product of the Becker and Tomes (1979) model implies a generational persistence term, g_m, which is a function of β and h and which describes the change in the income of the m-th generation household to a (compensated) change in the income of generation-0. In other words, g_m indicates the number of generations it takes for household income to regress back to the mean after a one-unit shock to the income of the generation-0 household. I specify g_m in Equation 20 (for the case where $\beta \neq h$). And in Figure 2, I illustrate three examples of g_m based on values I chose for β and h.

$$g_m = \frac{\beta^m - h^m}{\beta - h} \tag{20}$$

Evaluated together, g_m (Equation 20) and the IGE measure (Equation 19) offer a useful intuitive framework for interpreting intergenerational mobility: as $\beta, h \rightarrow 0$, g_m, IGE $\rightarrow 0$; and, as $\beta, h \rightarrow 1$, $g_m \rightarrow \infty$ and IGE $\rightarrow 1$. For example, in the case of low persistence ($\beta = .30, h = 0.10, IGE = 0.39$), the effect on household income of a one-unit increase in the income of the generation-0 household—the parent in this example—decays relatively quickly; the effect fades away in roughly seven generations. Whereas in the case of high persistence ($\beta = .90, h = 0.80, IGE = 0.98$), the effect of a one-unit increase in the income of the parent on the time path of income across generations decays relatively slowly; some portion of the effect remains

Figure 2: Intergenerational Time Paths of Income



fifty generations after the initial income shock for this case: the outcome of a child replicates her parent's almost completely and, so, the child is almost completely immobile. Thus, the effect of an increase (or decrease) in income on intergenerational persistence is strengthened by β and h.

In any case, Becker and Tomes (1979) assume perfect capital markets; household credit constraints do not bind. Generally speaking, credit constraints reduce a parent's propensity to invest in her child; thus, credit constraints effectively increase IGE. Becker and Tomes (1986) demonstrate this general relationship between imperfect capital markets and intergenerational mobility in a two-period model. I briefly reproduce the essential features of the model based on a version of it that Lee and Seshadri (2019) propose. In this version, a parent maximizes Equation 21, where c is consumption of the parent, $\bar{\theta}$ is her degree of altruism towards her child, c' is the consumption of her child, and $u(\cdot)$ is CRRA.

$$\max\{u(c) + \bar{\theta}u'(c')\} \tag{21}$$

The parent is subject to the budget constraints that I specify in Equations 22 and 23, where h is the parent's lifetime earnings, x is the parent's investment in the human capital of her child (h'), $(1 + r)$ is the gross interest rate on the investment, τ is a flat-tax rate used to fund a lump-sum transfer ($\bar{d}$) that the government invests in the human capital of the child, and s and s' are intergenerational transfers from grandparent to parent (s) and from parent to child (s').

$$c + \frac{s'}{(1+r)} = (1-\tau)(h-x) + s \quad \text{and} \quad c' = (1-\tau)h' + s' \tag{22}$$

$$h' = \bar{\zeta}a'(x + \bar{d})^{\bar{\gamma}} \quad \text{and} \quad s' \geq 0 \tag{23}$$

Therefore, the parent's disposable income takes the form of $(1 - \tau)h + s$. Her disposable income is partially consumed, c, and partially transferred to her child, s'. The production of human capital of the child (Equation 23) is a function of productivity ($\bar{\zeta}$) and the learning ability of the child (a'); returns to the production of human capital are diminishing ($\bar{\delta} < 1$). To solve the model, I assume $u(c) = \log c$, which yields Equation 24.

$$\max\{\log c + \bar{\theta}\log c'\} \tag{24}$$

To determine the choice variables c and x, the household satisfies the first-order conditions specified in Equations 25 and 26, where the right-hand side of Equation 26 is $\frac{\partial h'}{\partial x}$ with h' given by Equation 23.

$$s' : \frac{u'(c)}{\bar{\theta}u'(c')} \geq 1 + r \tag{25}$$

$$x : \frac{u'(c)}{\bar{\theta}u'(c')} = \frac{\bar{\gamma}\bar{\zeta}a'}{\left(x + \bar{d}\right)^{1-\bar{\gamma}}} \tag{26}$$

If the credit constraint does <u>not</u> bind ($s > 0$), Equation 25 holds with equality; the marginal rate of substitution of investment in the human capital of the child, x, equals the interest rate, and x^* is specified in Equation 27.

$$x^* = \left(\frac{\bar{\gamma}\bar{\zeta}a'}{1 + r}\right)^{\frac{1}{1-\bar{\gamma}}} - \bar{d} \tag{27}$$

In order to create the production of the human capital of the child as a function of the optimal lump-sum investment choice of the parent, I combine Equations 23 and 27 by eliminating x and taking logs, yielding Equation 28.

$$\log h' = \frac{1}{1 - \bar{\gamma}} \log\left(\bar{\zeta}a'\right) + \frac{\bar{\gamma}}{1 - \bar{\gamma}} \log\left(\frac{\bar{\gamma}}{1 + r}\right) \tag{28}$$

As the last step, I take the covariance of both sides of 28 with $\log h$. Doing so yields Equation 30, the IGE in terms of ρ_a.

$$IGE_{s>0} \xrightarrow{p} \frac{Cov(\log h, \log h')}{Var(\log h)} \tag{29}$$

$$\xrightarrow{p} \rho_a \tag{30}$$

Therefore, IGE is equal to the persistence of abilities, which is similar to the inheritability of endowments, h, in Becker and Tomes (1979).

On the other hand, if the credit constraint does bind ($s = 0$), Equation 26 yields Equation 31.

$$\bar{\zeta}a'(x + \bar{d})^{\bar{\gamma}}/(h - x) = \bar{\gamma}\bar{\theta}\bar{\zeta}a'/(x + \bar{d})^{1-\bar{\gamma}} \tag{31}$$

Thus, x^* is specified in Equation 32 where $\bar{\pi}$ is the fraction of a parent's earnings that the government transfers to her child: $\bar{d} = \bar{\pi}h$.

$$x^* = h\frac{\bar{\gamma}\bar{\theta} - \bar{\pi}}{(1 + \bar{\gamma}\bar{\theta})} \tag{32}$$

Combining Equations 23 and 32 by eliminating x and taking logs yields Equation 33.

$$\log h' = [\log \bar{\zeta} + \bar{\gamma}\log(\frac{\bar{\theta}(1 + \pi_d)}{1 + \bar{\theta}\bar{\gamma}})] + \bar{\gamma}\log h + \log a' \tag{33}$$

I subtract $\rho_a \log h$ from both sides. Additionally, I assume a long-run stationary equilibrium. Doing so yields Equation 34, where B is a constant and h_{-1} is the human capital of the grandparent.

$$\log h' = B + (\rho_a + \bar{\gamma})\log h - \rho_a\bar{\gamma}\log h_{-1} + \eta \tag{34}$$

I derive the IGE for the case of a binding credit constraint by taking the covariance of both sides of 34 with $\log h$. Doing so yields Equation 36.

$$IGE_{s=0} \xrightarrow{p} \frac{Cov(\log h, \log h')}{Var(\log h)} \tag{35}$$

$$\xrightarrow{p} \frac{\rho_a + \bar{\gamma}}{1 + \rho_a\bar{\gamma}} \tag{36}$$

The parameters in this model are functionally similar to β and h in the Becker and Tomes (1979) model: like β, γ reflects the amount the parent invests in her child; and like h, ρ reflects the persistence of inheritances or abilities. As $\rho, \gamma \to 0$, IGE $\to 0$; and, as $\rho, \gamma \to 1$, IGE $\to 1$. And, most importantly for my purposes in this thesis, $IGE_{s=0} > IGE_{s>0}$: credit constraints increase the IGE and, thus, decrease mobility.

3.2 Bernanke and Gertler: Aggregate Shocks and Credit Constraints

Credit rationing imposes credit constraints. Such rationing occurs when the demand for loanable funds is greater than the supply of loanable funds and information is incomplete and, thus, financial markets are imperfect (see for example, Akerlof 1970 and Stiglitz and Weiss 1981). A typical example of how credit rationing works includes a bank and a potential borrower. The bank considers a borrower to be high risk when the chance the borrower pays back the loan in full is low. Because the bank could lose income by making the loan, the bank prefers to lend instead to a low-risk borrower who is more likely to pay the loan back in full. Unfortunately, the bank cannot observe the riskiness of the borrower because information is asymmetric: the bank does not know whether a borrower is high or low risk.

If the bank charges a relatively high interest rate to all borrowers in order to compensate it for the risks it cannot observe, the bank unintentionally discourages low-risk borrowers, leaving mostly high-risk borrowers in the market for loans. Knowing this, the bank instead rations credit, effectively setting the interest rate below the market-clearing interest rate. Consequently, the demand for loanable funds exceeds the supply. Some borrowers receive loans while others, though apparently identical in terms of creditworthiness to those who receive loans, do not, no matter whether these excluded borrowers are willing to pay a higher (market-clearing) interest rate (Stiglitz and Weiss 1981). Thus, asymmetric-information problems impose so-called agency costs on the economy, where outcomes are second best to those in a world of perfect (symmetric) information.

Bernanke and Gertler (1989) reason that when an economy experiences a recession and, likely, a rise in asymmetric information, agency costs increase, heightening credit rationing and, ultimately, deepening the negative impacts experienced by the economy. Put differently, agency costs and the credit rationing associated with such costs are counter cyclical (Azariadis and Smith 1998). Indeed, according to Bernanke (1983), this pattern—a fall in intermediated credit to households caused by an adverse aggregate shock—made already-incomplete financial markets fragile during the Great Depression. Informational asymmetries caused intermediaries to ration credit, which led to a further contraction of the banking system. Due to the dramatic decrease in the amount and substantial increase in the price of loans, it became difficult for individuals dependent on loans, namely households, to secure them.

To demonstrate this relationship between aggregate shocks and credit rationing, Bernanke and Gertler (1989) propose a real business cycle overlapping-generations model in which aggregate economic shocks—the sort that propagate business cycles—buffer the economy's production function. In effect, a negative (positive) shock decreases (increases) internal-financing capacity—net worth in, say, the form of savings—and, in doing so, increases (decreases) agency costs. In this model, every borrower has an investment project of which only they *costlessly* know the outcome. Others, namely lenders, must incur a cost, γ, to know the outcome of a project; thus, agency problems require costly state verification.

A borrower is characterized by their efficiency, ω, which ranges between 0 and 1; a relatively efficient borrower uses fewer resources to invest in their project and therefore the borrower is characterized by a low ω. Equation 37 specifies the supply of loanable funds in an economy with perfect information, $\gamma = 0$, where $\hat{q}_{t+1}$ denotes the expected price of capital, k_{t+1} denotes next period's capital stock, κ is the possible outcome of a project, r denotes the marginal rate of return, and x is a function of ω and denotes project inputs for a borrower with efficiency ω.

$$\hat{q}_{t+1} = rx(k_{t+1}/\kappa\eta)/\kappa \tag{37}$$

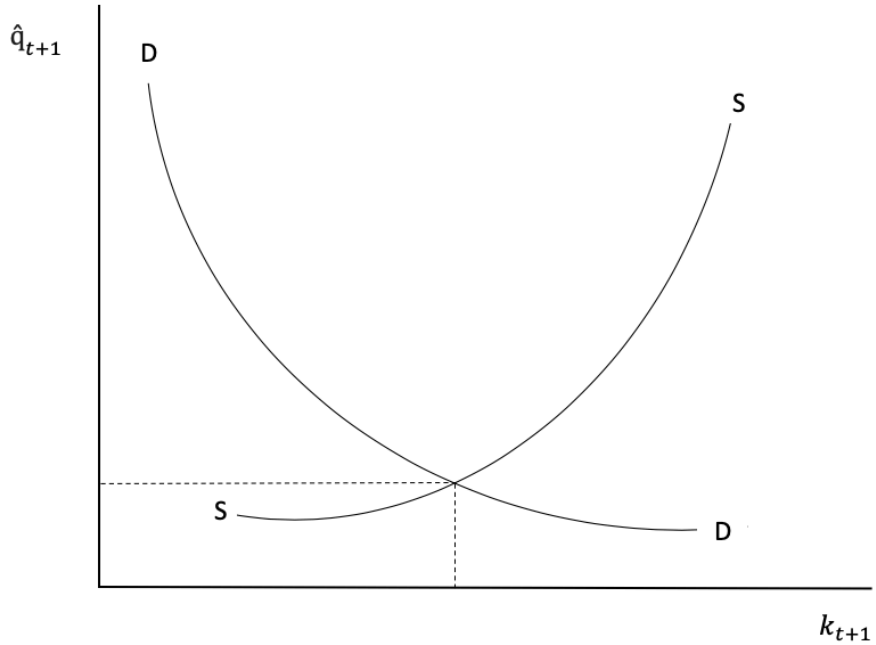
When the expected price of capital ($\hat{q}_{t+1}$) increases, individuals decrease their consumption and increase saving; capital formation and, thus, k_{t+1} increases. Equation 38 specifies the demand loanable funds, where the expected price of capital equals the expected marginal product of capital, $f'(k_{t+1})$, times a random aggregate productivity shock, θ, which is the source of aggregate fluctuations in the model.

$$\hat{q}_{t+1} = \theta f'(k_{t+1}) \tag{38}$$

The price and amount of capital for the next period are determined by the intersection of the supply curve (Equation 37) and the demand curve (Equation 38). In an economy with perfect information, $\hat{q}$ and k are constant. In Figure 3, I illustrate this equilibrium outcome. The perfect-information outcome depicted in Figure 3, in which a constant (steady-state) level of investment prevails over time, establishes a benchmark example against which to compare the effects from an aggregate shock in the imperfect-information case.

In an economy with imperfect information, $\gamma > 0$, Bernanke and Gertler (1989) propose that the outcome of each project will either be a bad outcome, κ_1, or a good outcome, κ_2. The probability of each outcome is π_1 and π_2 respectively, where $\pi_2 = 1 - \pi_1$. The project of each individual requires inputs that exceed his savings, $x(\omega) > S^e$, therefore, he borrows the difference, $B = x(\omega) - S^e$. The individual seeks to maximize his next period consumption and borrows to invest in a project in order to do so. The borrower knows the outcome of his project and the lender does not.

Figure 3: Capital market with Perfect information ($\gamma = 0$)



Therefore, the lender identifies the expected agency costs, which are determined by the likelihood a project fails and whether or not the lender spends γ to learn the outcome of the project.

In the model, expected agency costs increase as savings decrease. Therefore, an adverse shock that decreases net worth causes the agency costs of intermediation to increase. The increase in agency costs increases the amount of return a lender requires, which decreases the efficiency (ω) of the pool of borrowers. A large number of borrowers with a higher ω (less efficient) discourage the lender, who expects to earn less due to a more risky pool of lenders; this outcome decreases the amount of credit the lenders provide. The level of investment falls, which further perpetuates the negative effects of the aggregate shock. Thus, the adverse aggregate shock causes savings to decrease, shifting the supply curve of loanable funds to the left. In Figure 4, I illustrate the perfect information ($\gamma = 0$) supply curve, SS, with the imperfect information ($\gamma > 0$) supply curve, S'S', and the demand curve, which is unaffected by imperfect information.

Figure 4: Capital market with imperfect information ($\gamma > 0$)

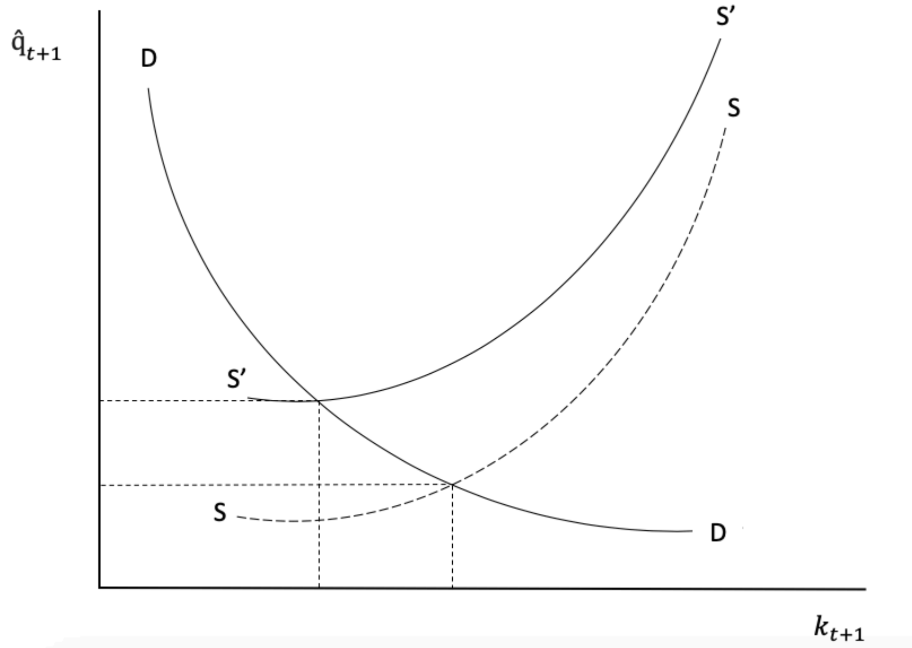


Figure 4 demonstrates the reduction in supply by the shift from SS to S'S' due to imperfect information. Ultimately, in the case of imperfect information, a low level of savings increases agency costs and leads to a decrease in the number of profitable projects, causing SS to shift left to S'S' and decreasing the equilibrium capital stock.

In summary, in this model, an adverse aggregate shock decreases net worth, causing the agency costs of intermediation to increase and lowering the level of investment as credit constraints imposed on credit-rationed borrowers tighten. Based on the models I present in this chapter, I reason that variation in credit constraints caused by aggregate economic shocks experienced differently across states (something I demonstrate in Chapter 4) contribute meaningfully to the variation in intergenerational mobility that we observe across states. Essentially, an aggregate shock affects the amount a parent can invest in the human capital of their child, which, in turn, affects the economic mobility of that child.

4 Heterogenous State-Level Economic Behavior

By definition, an aggregate economic shock affects everyone—and, so, every state—in the economy. Nevertheless, in this section, I demonstrate that at any moment in time, shocks to the United States economy affect states differently. Economists often measure economic fluctuations, or business cycles, at the national level using macroeconomic variables such as real gross domestic product (GDP), the unemployment rate, and real personal income. Generally speaking, a business cycle is an irregular and unpredictable short-run aggregate economic fluctuation; the phases of the business cycle include peak, recession, trough, and expansion.

The National Bureau of Economic Research (NBER) defines a recession as a significant decrease in economic activity across the nation that persists for multiple months. Business cycles in the United States are well specified by the NBER, which publishes nationally recognized business cycle dates. On the other hand, business cycles of individual states within the United States are not well specified; we lack a nationally recognized measure of state-level business cycles, which can differ markedly from the national business cycle. The timing, amplitudes, and durations of a business cycle—an ostensibly macroeconomic feature instigated by aggregate shocks—are not uniform across states (or, in all likelihood, regions within a state). So, while the effects of aggregate shocks to the economy are typically studied at the national level, the effects of such shocks are in fact felt quite differently across the fifty states. At best, the U.S. Bureau of Economic Analysis groups states into economic regions that experience similar economic activities. Relatively few studies examine—and, so, shed light on—heterogenous state-level economic behavior.

Crone (2005) finds that within each of the eight BEA-determined regions, each of which include multiple states grouped together based on socioeconomic outcomes, state-level business cycles differ. In order to find state-level cyclicality, the author de-trends a state-level coincident index, which consists of 3 monthly state-level variables, and compares the cyclical component of each state to the national business cycle. The business cycles of some states largely reflect the business cycle of the national economy, as expected. Meanwhile, the business cycles of other states are quite varied: recessions are longer, more frequent, and deeper, for example. Indeed, although the author's objective is to demonstrate homogeneity across state-level business cycles, his study emphasizes the difficulty in doing so. The New England region—including Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut—has the strongest cohesion index of 0.91, which the author measures through cluster analysis. The Southwest region—including Texas, Oklahoma, New Mexico, and Arizona—has the weakest cohesion index of 0.55.

The state-level unemployment rate is another macroeconomic variable that differs greatly from one state to another. With the intent to improve national fiscal policy, Elmendorf and Dynan (2019) examine the movement of national- and state-level unemployment rates to compare the volatility of these movements across states and the national economy. The low-to-high range of national unemployment rates over the last three decades spanned 6.5 percentage points; meanwhile, the range of state-level unemployment rates collectively spanned 12.5 percentage points, this after excluding outliers. Moreover, states occasionally experience an increase in unemployment significant enough to signal a recession at the state level, even while the nation experiences growth. For example, during the 1980s, many oil-producing states, including Oklahoma, Texas, and Wyoming, effectively entered recession while the national economy did not (Elmendorf and Dynan 2019).

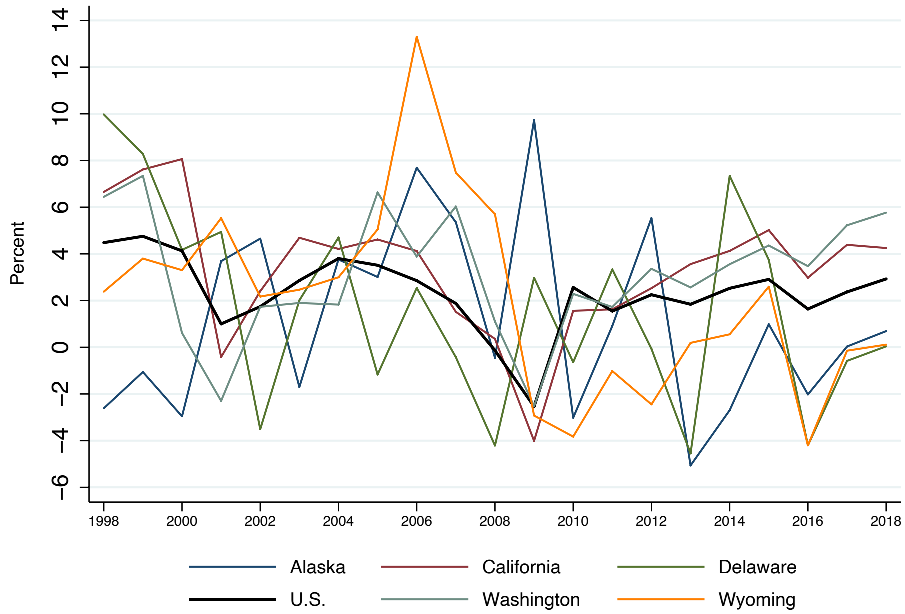
Finally, Owyang, Rapach, and Wall (2009) use a dynamic factor model in order to address the incomplete information that comes from analyzing the United States economy through a national lens. The authors use state-level real personal income and state-level employment growth to demonstrate the heterogeneity that exists across state economies. The authors determine that three of the factors they create explain a sizable portion of the heterogeneity of state-level variables and so too business cycles. Specifically, the business cycle factor is closely related to the real personal income growth variable with a statistically significant correlation coefficient of 0.77. The authors specify the heterogeneity across states through the growth of real personal income as well as a new business cycle factor, showing that states not only vary from the national business cycle, but also other states. This heterogeneity is masked by analyzing the business cycle as an aggregate of state economies, therefore limiting the ability of aggregate variables to fully represent the state of the nation's economy (Owyang, Rapach, and Wall 2009).

To demonstrate the variability of state-level economic outcomes, I focus for now on real gross state product (GSP), which measures the level of economic output within state borders. Appropriately transformed, real GSP can reveal state-level business cyclicality. The Bureau of Economic Analysis provides quarterly data for this measure for each of the 50 states. The population size of each state affects the level of GSP and, so, comparing the economic output of, for example, California to that of Delaware is not appropriate. So, I use the growth rate of the GSP of each state, a common method of addressing this size difference, so that I can compare state-level economic fluctuation across states.

In Figure 5, I illustrate the annualized (same-month) growth rate of GSP, for select states and the nation (in which case I use GDP); the heterogeneity of state-level economic fluctuations is readily apparent. When the growth rate of GSP measures zero percent, the level of GSP from one quarter to the next is unchanged. When the growth rate is above (below) zero percent, GSP grew (fell) in relation to GSP in the prior quarter.

Figure 5 depicts multiple instances where an individual state's GSP growth deviates from GSP growth of other states and national GDP growth. In regard to the

Figure 5: Real GDP and Real GSP, Select States

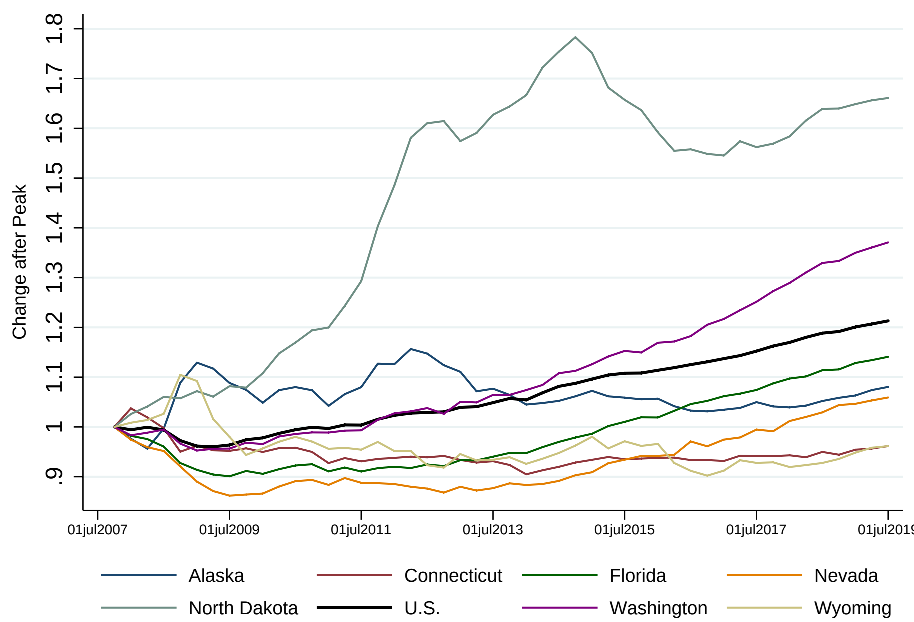


timing of fluctuations, for example, initially the growth rate of GSP in Alaska registers approximately negative 2 percent while the growth rate of GDP for the national economy registers approximately positive 2 percent. Additionally, while the growth rate of national GDP falls beginning in 2008, indicating a decline in the production of GDP at the national level, the growth rates of GSP in some states, namely Delaware and Washington, continue to register positive values until 2010, at which time the growth rate of national GDP is once again positive.

In addition to the timing of state-level business cycles, Figure 5 clearly illustrates the differences in the magnitude of GSP growth across the states. For example, in 1998, when the level of GSP in Alaska fell by around 2 percent, Washington experienced a 10 percent rise in GSP; this 12 percentage point dispersion exemplifies the large difference in the magnitude of growth experiences across the states. Similarly, during the recession in 2008, when the level of GSP in Alaska rose by around 10 percent, most other states experienced a significant fall in GSP.

In order to demonstrate the variation in duration of business-cycle phases, such as recessions and expansions, I illustrate in Figure 6 GSP relative to its respective value in December 2007, the NBER-designated date of the national business-cycle peak just before the Great Recession. This measure represents the economic performance of the state, across time, as a percentage of a single point in time, thus demonstrating how each state experienced the aftermath of the Great Recession. When this measure registers 1, the economic output of the state is equal to that of its December 2007 level. Similarly, when this measure registers below (above) 1, economic output is below (above) the level of GSP that the state's economy achieved in December 2007. Therefore, when this measure is below (above) 1, the state economy is contracting (expanding) relative to its size in December 2007.

Figure 6: GSP since December 2007, Select States



According to Figure 6, while national economic output fell for several quarters after the business cycle peak in December 2007, the recession did not negatively affect economic fluctuations in some states (North Dakota and Alaska) while others have yet to reach their respective pre-recession levels of GSP (Connecticut and Wyoming). For the states that experienced a fall in GSP, the duration of the fall differed across these states. The United States economy as a whole recovered its pre-recession level of economic activity around July 2011, and Washington followed suit. In contrast, Florida did not recover (in this sense) until July 2015 and Nevada recovered yet another two years after that. Clearly, states experienced very different outcomes in regard to the lengths of contractions during the most recent recession.

For a clearer understanding of state-level business cyclicality, and in order to obtain the working measure of state-level business cyclicality that I use in my panel regression analysis that I discuss in Chapter 5, I isolate the cyclical component from the trend component of national and state-level output measures. In general, the trend component measures the balanced- (or steady-state-) growth path of the economy in the long run, when market-clearing prevails; the Solow growth model, for example, describes this pattern of growth of the economy. Meanwhile, the cyclical component measures the business cycle. In applied macroeconomics, a conventional method of decomposing a time series, such as output, into its trend and cyclical components is the Hodrick-Prescott filter (hereafter, HP filter), which extracts—that is, filters—the trend component from the time series; the cyclical component is simply the difference between the time series and its trend component (Hodrick and Prescott, 1997).

More formally, consider a times series, x_t, that includes a trend component, x_t^τ; additionally, suppose the series includes $T+1$ observations, from observation 0 to observation T. The HP-filter determines the series, x_t^τ, that minimizes Equation 39, where $\lambda \geq 0$ (Challe 2019).

$$HP = \sum_{t=0}^{T} \left(x_t - x_t^\tau\right)^2 + \lambda \sum_{t=1}^{T-1} \left[\left(x_{t+1}^\tau - x_t^\tau\right) - \left(x_t^\tau - x_{t-1}^\tau\right)\right]^2 \qquad (39)$$

The first term in Equation 39 expresses the cyclical component, the difference between the time series (x_t) and its trend component (x_t^τ); the smaller the magnitude of the first term, the less smooth the trend component, which in this case more or less mimics the actual time series. The second term in Equation 39 expresses the smoothness (over time) of the trend component; the smaller the magnitude of $\sum_{t=1}^{T-1}\left[\left(x_{t+1}^{\tau}-x_{t}^{\tau}\right)-\left(x_{t}^{\tau}-x_{t-1}^{\tau}\right)\right]^{2}$, the smoother the trend component. Imagine, for example, that the solution series, x^{τ}, sets $\left(x_{t+1}^{\tau}-x_{t}^{\tau}\right)=\left(x_{t}^{\tau}-x_{t-1}^{\tau}\right)$ for all t; in this case, the trend component is linear.

Thus, minimizing Equation 39 imposes a trade-off: as the magnitude of the first term decreases, the smoothness of the trend component decreases (because in this case the trend component converges on the original time series); as the magnitude of the second term decreases, the smoothness of the trend component increases. The term λ determines this trade-off: a relatively large magnitude for lambda causes a relatively smooth trend; as λ approaches ∞, the trend component becomes linear. Conventional settings for λ are $\lambda = 100$ (annual data), $\lambda = 1600$ (quarterly data), and $\lambda = 14400$ (monthly data); I follow this convention.

To demonstrate the effects of this filtering process, in Figure 7 I illustrate United States GDP for the period 1948Q1 through 2020Q1 and its corresponding HP-filtered trend component—x_t^{τ} in the context of Equation 39. In Figure 8, I illustrate, for the same GDP series, the cyclical component as a share of the trend component—$\left(x_t - x_t^{\tau}\right)/x_t^{\tau}$ in the context of Equation 39. This latter share measure is my working measure of business cyclicality that I use going forward to estimate and compare across states cyclical fluctuations in a given business-cycle time series such as GSP and state-level real personal income.

In Table A1, I report the correlation matrix of the cyclical component of real GSP of each state. The correlation between the cyclicality of each state and the cyclicality of the GDP of the United States varies greatly between states. For only 17 states does the correlation coefficient measure 0.8 or above, signaling a strong correlation between the cyclicality of the GSP in these states and the cyclicality of GDP.

Figure 7: Trend Component; United States GDP

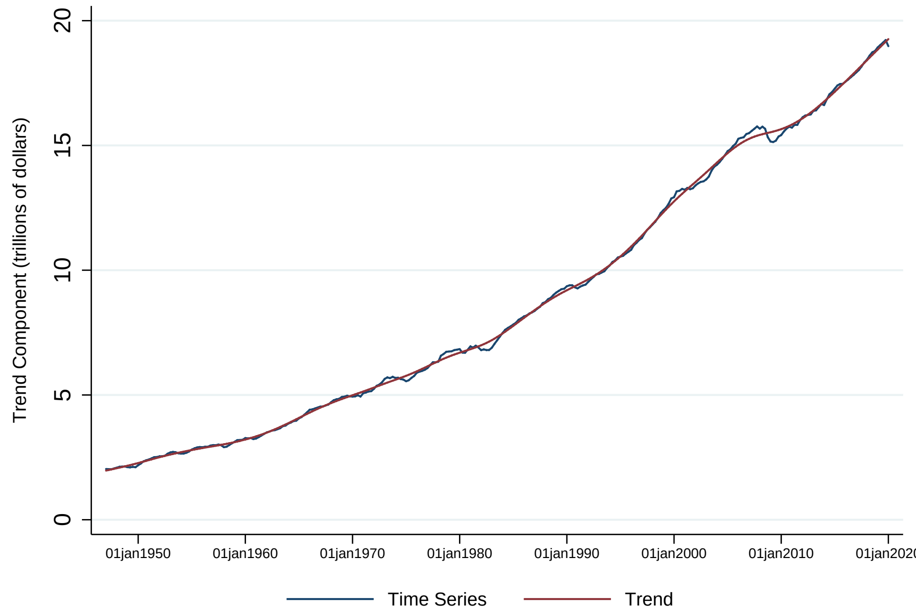
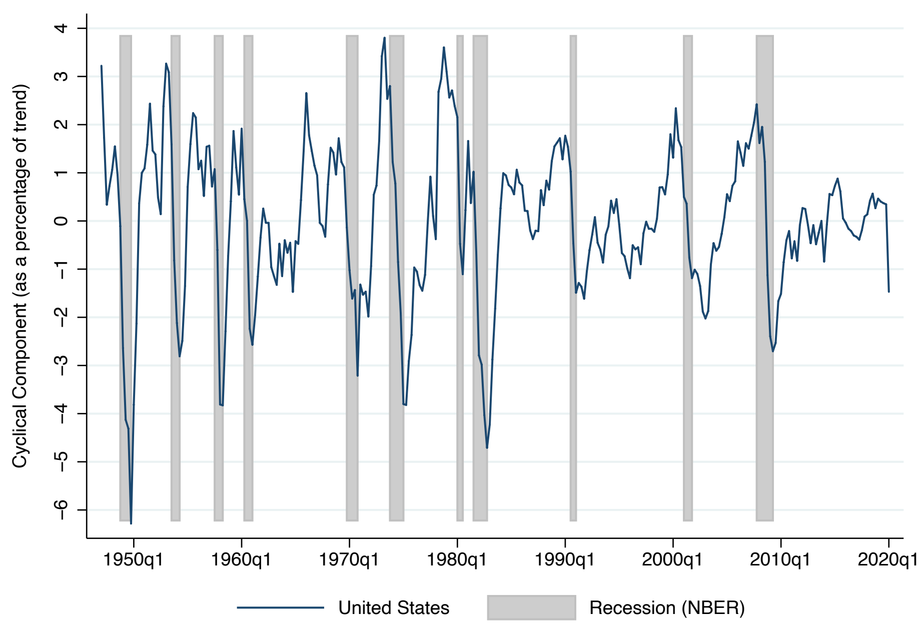


Figure 8: Cyclical Component; United States GDP



Unfortunately, state-level GSP data begin in the first quarter of 2005. Although GSP is the most accepted measure of the economic performance of a state, the measure is not available for the timeframe that I need in order to include in my analysis birth cohorts from 1950 through 1980. In order to measure the cyclicality of state-level economic performance around the time of these birth cohorts, I use real total personal income. I construct this measure by dividing nominal total personal income, which the Federal Reserve Economic Database provides at a quarterly frequency from 1948 to 2019, by the consumer price index. Real total personal income is a reasonable proxy for real GSP. Indeed, the two series are highly correlated.

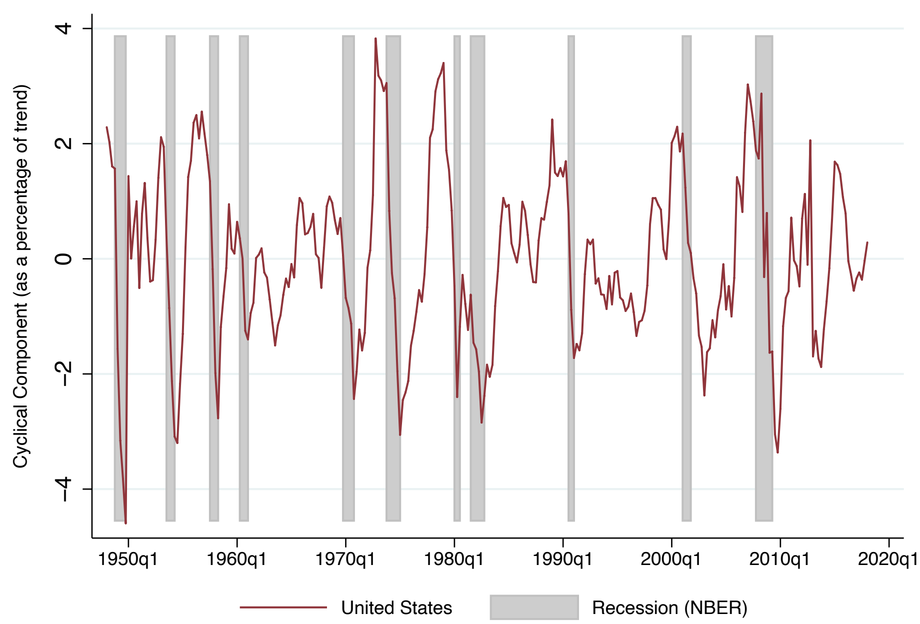
In Table 1, I report, for each state and the nation, correlation coefficients between real GSP and real total personal income in levels (column 1), HP-filtered trend components (column 2), HP-filtered cyclical components (column 3), and the ratio of the cyclical to trend components (column 4; my working measure of business cyclicality). For forty states and the nation as a whole (based on the levels of real GDP and national real total personal income), I report a correlation coefficient above 0.9.

Table 1: Correlations of State-Level and National Real Personal Income

	Levels	Trends (t)	Cycles (c)	c/t	$\%\Delta t$	$\%\Delta$ Levels
AL	0.910	0.953	0.490	0.495	0.589	0.566
AK	0.703	0.819	0.088	0.074	0.872	0.224
AZ	0.951	0.949	0.731	0.735	0.885	0.855
AR	0.945	0.987	0.414	0.434	0.603	0.356
CA	0.990	0.997	0.618	0.632	0.971	0.710
CO	0.992	0.998	0.709	0.716	0.943	0.758
CT	-0.058	-0.501	0.620	0.637	0.808	0.614
DE	0.646	0.902	0.657	0.655	0.307	0.553
FL	0.934	0.913	0.696	0.706	0.934	0.828
GA	0.981	0.984	0.666	0.674	0.969	0.713
HI	0.978	0.988	0.461	0.466	0.516	0.526
ID	0.977	0.987	0.542	0.560	0.945	0.594
IL	0.973	0.998	0.736	0.744	0.906	0.707
IN	0.937	0.996	0.456	0.483	0.954	0.455
IA	0.960	0.990	0.609	0.618	0.284	0.511
KS	0.942	0.972	0.675	0.708	0.322	0.664
KY	0.929	0.990	0.367	0.392	0.664	0.404
LA	-0.478	-0.756	-0.034	-0.054	-0.585	0.090
ME	0.873	0.910	0.385	0.389	0.993	0.517
MD	0.985	0.998	0.578	0.577	0.760	0.495
MA	0.989	0.997	0.627	0.624	0.939	0.627
MI	0.876	0.912	0.704	0.721	0.990	0.788
MN	0.985	0.997	0.551	0.571	0.971	0.592
MS	0.642	0.855	0.402	0.398	0.661	0.451
MO	0.944	0.993	0.316	0.320	0.853	0.396
MT	0.991	1.000	0.755	0.751	0.850	0.770
NE	0.981	0.998	0.528	0.538	0.899	0.522
NV	0.816	0.740	0.636	0.642	0.919	0.846
NH	0.987	0.999	0.663	0.669	0.960	0.661
NJ	0.906	0.956	0.536	0.539	0.981	0.504
NM	0.929	0.956	0.611	0.591	0.331	0.592
NY	0.957	0.987	0.349	0.340	0.159	0.353
NC	0.981	0.996	0.601	0.609	0.902	0.555
ND	0.991	0.998	0.874	0.832	0.989	0.877
OH	0.953	0.976	0.650	0.660	0.992	0.639
OK	0.928	0.971	0.704	0.708	0.633	0.711
OR	0.992	0.998	0.780	0.787	0.963	0.801
PA	0.988	0.998	0.612	0.611	0.971	0.587
RI	0.782	0.883	0.531	0.541	0.931	0.552
SC	0.982	0.989	0.650	0.669	0.950	0.640
SD	0.979	0.994	0.679	0.686	0.828	0.653
TN	0.979	0.988	0.549	0.553	0.976	0.565
TX	0.990	0.996	0.676	0.668	0.136	0.540
UT	0.995	0.999	0.789	0.807	0.959	0.819
VT	0.928	0.992	0.332	0.315	-0.231	0.363
VA	0.976	0.997	0.431	0.436	0.568	0.467
WA	0.995	0.999	0.761	0.788	0.952	0.775
WV	0.941	0.998	0.586	0.580	0.897	0.606
WI	0.979	0.995	0.595	0.604	0.948	0.553
WY	0.270	0.262	0.521	0.535	0.719	0.621
US	0.995	0.999	0.760	0.770	0.964	0.748

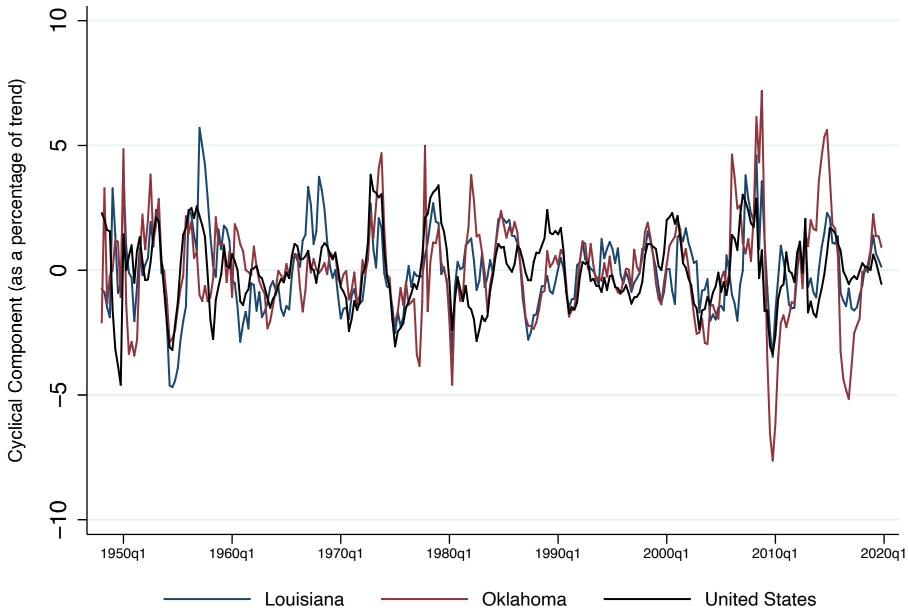
In Figures 9 and 10, I illustrate the cyclical to trend components of real personal income for the national economy (Figure 9) and select states (Figure 10). According to Figure 9, cyclical fluctuations in U.S. real personal income closely correspond to NBER business-cycle phases: as the nation falls into an NBER-identified recession, for example, the cyclical component of U.S. real personal income falls as well. Thus, my working measure of business cyclicality is suitable for my purposes. Moreover, as with real GSP, state-level real personal income varies substantially across states. According to Figure 10, the cyclical components (as a percentage of the trend components) of Louisiana and Oklahoma differ in magnitude as well as direction. For example, around 1957, the cyclical component for Louisiana is positive, which signals an expansion, while the cyclical component for Oklahoma is negative; meanwhile, the corresponding measure for the United States is zero. Such variation between states is apparent across all 50 states through time.

Figure 9: Cyclical Fluctuations in U.S. Real Personal Income



In Tables 2 and 3, I report summary statistics of the variation across states of state-level real total personal income during NBER-identified recessions (Table 2)

Figure 10: Cyclical Fluctuations in U.S. Real Personal Income



and expansions (Table 3). Specifically, I report the standard deviation and the coefficient of variation for the growth rate of real personal income across the individual states in order to demonstrate state-level variation across business cycles. In Table 2, the average growth of real personal income is negative, which indicates a recession. The coefficient of variation—the standard deviation relative to the mean—during recessions is mostly above one, which indicates relatively high variation. The high variation of real personal income during periods of recession demonstrates the vastly different experiences across the individual states.

In Table 3, the coefficient of variation during expansions is mostly below one, which indicates relatively low variation. During expansions, the variation decreases and state-level economic fluctuations are less divergent. The coefficient of variation for the mid 1970s through the 1980s is above one potentially because the expansions during this time were not very large or long lived. In any case, though the variation decreases during times of expansion, it does not disappear, implying that state-level cyclical variations are present during both recession and expansion phases of the

Table 2: State-Level Real Personal Income Performance during National Recessions

Start	End	Max.	Min.	Avg.	St. Dev.	C.V.
Q3-1953	Q2-1954	11.886%	-9.607%	0.772%	4.173%	5.406
Q4-1957	Q2-1958	12.950%	-7.945%	0.212%	3.678%	17.333
Q3-1960	Q1-1961	18.558%	-3.346%	3.213%	4.261%	1.326
Q1-1970	Q4-1970	10.070%	-3.244%	3.103%	2.610%	0.841
Q1-1974	Q1-1975	16.706%	-16.632%	-0.898%	4.780%	5.326
Q2-1980	Q3-1980	3.757%	-18.656%	-2.757%	3.798%	1.378
Q4-1981	Q4-1982	16.341%	-4.902%	1.025%	3.319%	3.238
Q4-1990	Q1-1991	3.841%	-5.561%	-0.946%	1.890%	1.999
Q2-2001	Q4-2001	3.353%	-2.449%	0.667%	1.224%	1.835
Q1-2008	Q2-2009	6.695%	-6.133%	-0.408%	2.557%	6.272

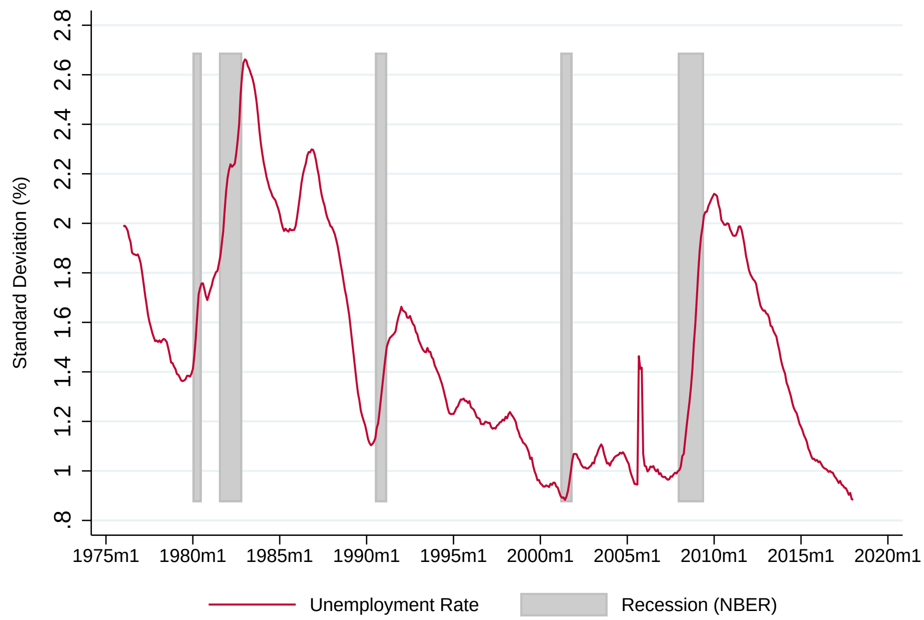
business cycle.

Table 3: State-Level Real Personal Income Performance during National Expansions

Start	End	Max.	Min.	Avg.	St. Dev.	C.V.
Q1-1950	Q2-1953	22.012%	-6.589%	6.611%	5.100%	0.771
Q3-1954	Q3-1957	14.336%	-5.111%	4.984%	3.802%	0.763
Q3-1958	Q2-1960	12.837%	-6.910%	3.851%	3.676%	0.955
Q2-1961	Q4-1969	14.386%	-3.768%	4.966%	3.158%	0.636
Q1-1971	Q4-1973	20.459%	0.923%	6.351%	3.380%	0.532
Q2-1975	Q1-1980	13.191%	-6.676%	2.868%	3.203%	1.117
Q4-1980	Q3-1981	14.745%	-7.584%	1.816%	3.428%	1.887
Q1-1983	Q3-1990	8.444%	-4.550%	3.219%	2.512%	0.780
Q2-1991	Q1-2001	7.666%	-1.498%	3.133%	1.815%	0.579
Q1-2002	Q4-2007	8.183%	-1.484%	2.416%	1.955%	0.809

Finally, another common indicator of economic activity is the unemployment rate. The unemployment rate is a reliably countercyclical measure of aggregate economic fluctuations. Nevertheless, state-level unemployment rates vary substantially across states. In fact, Dynan and Elmendorf (2019) use the state-level population weighted unemployment rate to highlight the differences in cyclical outcomes across states, and to emphasize the importance of recognizing this heterogeneity when crafting macroeconomic stabilization policies. In Figure 11, I illustrate the monthly standard deviation of state-level unemployment rates, along with NBER recession bars. When the national economy is in recession, the standard deviation across states increases, reflecting the varied state-level responses to adverse aggregate shocks.

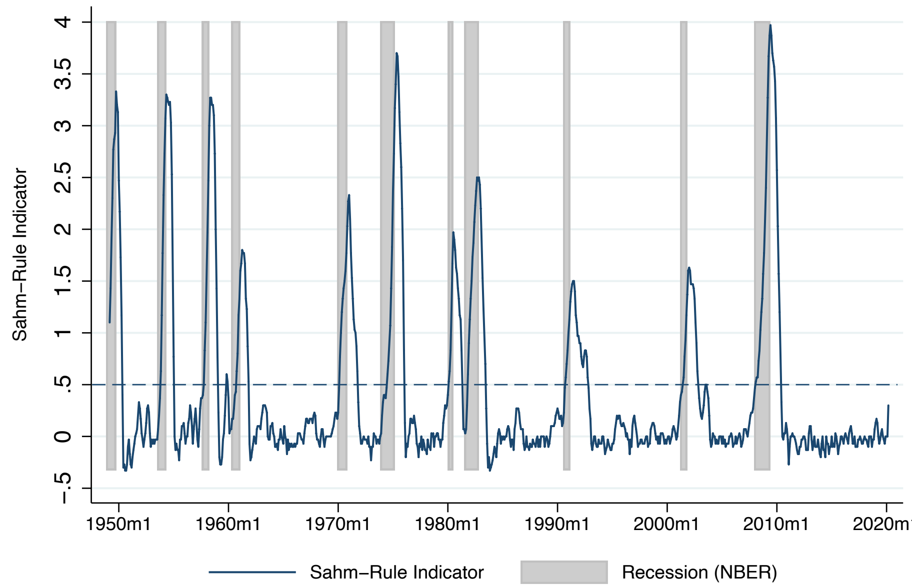
Figure 11: Standard Deviation of State Unemployment Rates



The unemployment rate proves insightful for understanding state-level economic fluctuations in yet another way. In 2019, Claudia Sahm, director of macroeconomic policy at the Washington Center for Equitable Growth and formerly with the Board of Governors of the Federal Reserve System, developed an elegant recession-warning indicator that, according to the Federal Reserve Bank of St. Louis, "signals the start of a recession when the three-month moving average of the national unemployment rate rises by 0.50 percentage points or more relative to its low during the previous 12 months." The Sahm recession indicator, coined the Sahm rule, is now a standard fixture of reduced-form recession indicators. In Figure 12, I illustrate the Sahm rule for the national economy; the strength of the relationship between the rule and recessions is evident: the Sahm rule consistently registers above 0.5 at the beginning of each NBER-indicated recession.

I reason that this tool can be applied to state-level unemployment rates in order

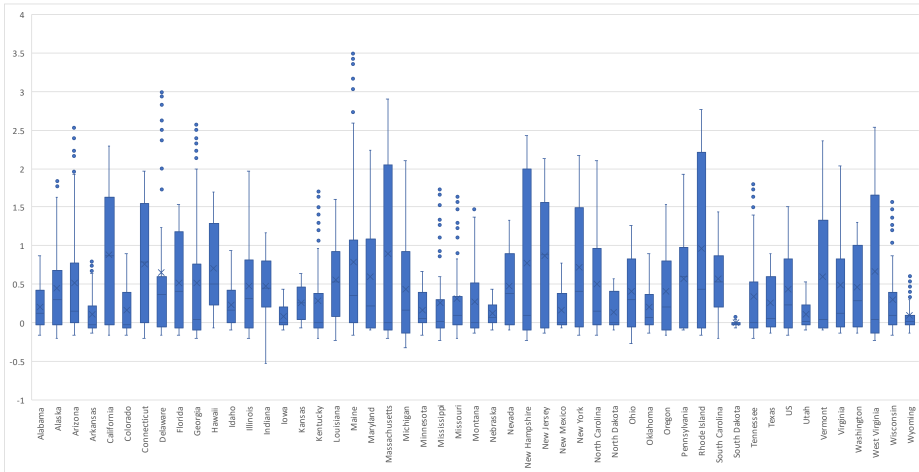
Figure 12: Sahm Recession Indicator for the United States



to identify state-level business cycles and, ultimately, to illustrate how these cycles vary across states. I use the Sahm-rule formula with state-level unemployment rates to identify state-level recessions. In Figure 13, I illustrate the Sahm rule applied to monthly state-level unemployment rates, from 1990 to 1994. This period includes a national recession. Above the name of each state along the horizontal axis are the Sahm rule values during the 60 months that span 1990 to 1994; each box indicates the middle quartile of the Sahm rule values, the top and bottom segments represent the top and bottom quartiles, and a dot outside a whisker is an outlier. For example, based on the Sahm rule, the monthly unemployment rate in Maine places that state in recession in 24 of the 60 months from 1990 to 1994. On average, from 1990 to 1994, the state-level Sahm rule indicates a recession in 19 of the 60 months for a given state.

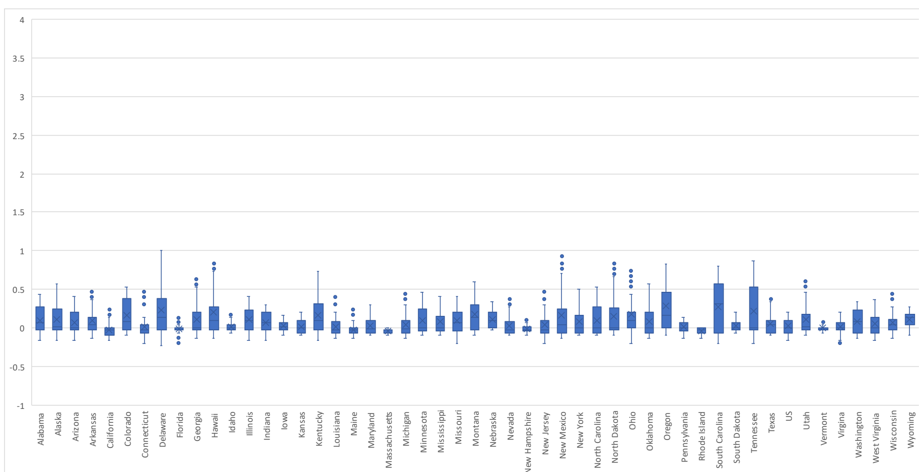
In Figure 14, I illustrate the Sahm rule for the years 1995 through 1999, a span of time when the national economy expanded. During a national expansion, not surprisingly, the Sahm rule does not signal recession for the national economy but this is not the case for all fifty states. For nineteen states, there are several months during which the Sahm rule signals recession. For example, in the case of South

Figure 13: Sahm Recession Indicator, State Level, 1990 through 1994



Carolina, the Sahm rule signals 20 (of 60) months of recession.

Figure 14: Sahm Recession Indicator, State Level, 1995-1999



In summary, using several different measures of state-level aggregate economic fluctuations, I am able to demonstrate the heterogeneous nature of state-level economic fluctuations. This state-level heterogeneity, like the state-level heterogeneity of rates of absolute income mobility, occurs through time, affording me a panel dataset and the opportunity to test my central hypothesis that aggregate economic fluctuations affect intergenerational mobility. Essentially, states experience economic shocks differently, resulting, according to my argument in Chapter 3.2, in differing credit constraints across states and time, causing state-level variation in intergenerational economic mobility.

5 Empirical Results

5.1 Data

In this section, I define and discuss the measures I use in my panel regression equations. Then, I discuss my empirical results of tests of the relationship between aggregate economic performance and the rate of absolute income mobility, both of which I measure across states and time. This is to say, I test my central hypothesis that business cycles drive intergenerational-mobility outcomes of children, conditional on the income percentile rank of their parents. I reason that low economic performance tightens borrowing constraints, thus restricting the amount a parent invests in the human capital of her child and, consequently, limiting the foundational skills and the expected earnings of the child.

My first independent variable is the average ratio of cyclical to trend components of state-level real personal income. I construct this variable using the HP-filter, as I discuss in Chapter 4, on quarterly data for real personal income from 1950 to 1989. I divide the cyclical component by the trend component because the cyclical component of real personal income for each state varies in magnitude across states due to the different sizes and populations of the states. Dividing the cyclical component by the trend component creates a standardized and easily interpreted measure: the ratio of cyclical to trend components is positive during expansions and negative during recessions. Additionally, the measure is scaled by the respective state-level long-run trend, which is relatively similar across states.

For each state and birth cohort, I average the ratio of cyclical to trend components for the foundational years of the childhood—the decade following the year indicating the birth cohort. For example, for a given state and, say, the 1950 birth cohort, I average the ratio of cyclical to trend components from 1950 to 1959, during which the age of a child in the 1950 birth cohort ranges anywhere from 0 (born in 1950) to 18 (born in 1941). Because my mobility measures rely on census data, the children in birth-cohort Year-x were born anytime between Year-x minus 9 years and Year x. Importantly, no observations associated with a particular birth-cohort average of the ratio of cyclical to trend components overlap with the observations of another birth-cohort average associated with the same state: for example, the observations associated with the average ratio of cyclical to trend components for the 1950 birth cohort span 1950 to 1959; the comparable range for the 1960 birth cohort spans 1960 to 1969.

Additionally, I construct a five-year average as well: for example, for birth cohort 1950, I average the ratio of cyclical to trend components from 1950 to 1954, during which the age of a child in the 1950 birth cohort ranges anywhere from 0 (born in 1950) to 13 (born in 1941). This is my second independent variable. Finally, my third independent variable is the average state-level unemployment rate, a mean-reverting (stationary) series that I do not filter or otherwise transform in any way.

Crime rates are a potential determinant of mobility that may be correlated with the business cycle; if so, excluding the crime rate would create an omitted variable bias when regressing state-level mobility on the cyclical component of real personal income. In order to address this issue, I include both property and violent crime as explanatory variables in my regression. Since 1960, the Justice department provides the annual property and violent crime rates of each state per 100,000 individuals. I average the state-level crime rates that each family experiences during the foundational years of the child. For example, for the 1960 birth cohort, I average the state-level crime rates between the years 1960 and 1969.

My dependent variable is the state-level rate of absolute income mobility conditional on parental income percentile rank for the birth cohorts 1950, 1960, 1970, and 1980 (see Equation 5 and, for example, Figure 1). I retrieve these data from the datasets and code that accompany Chetty et al. (2017). The authors use decennial census data and Current Population Survey data in order to measure the marginal distribution of income for both parents and children. These cross-sectional data allow the authors to measure the household income for parents and children when they are about 30 years old, adjusting for inflation. Additionally, Chetty et al. (2017) use data from de-identified tax returns and measure household income as pre-tax income filed on tax returns. Using all these data, the authors are able to link parents to children and calculate the rate of absolute income mobility.

Each of the state-level rates of absolute income mobility for the birth cohorts 1950, 1960, 1970, and 1980 represents the probability a child born in the corresponding state and cohort, say 1950, will earn a larger income than her parent did, conditional on her parental income percentile rank when she was born. In Figures 15 through 18, I illustrate the downward trend and interstate variability of this measure over time throughout the United States for the 1950, 1960, 1970, and 1980 birth cohorts, for parental percentile rank 50 $\left(A_{1950,\widetilde{50}}\right)$. (For example, the rates associated with South Dakota in Figures 15 and 18 correspond to the y-axis values for the 1950 and 1980 birth cohorts at parental percentile rank 50 in Figure 1). In these figures, the areas that appear darker have the highest percentage of children who earn more income than their parents did. Across the United States, mobility for the 1950 birth cohort (Figure 15) is similar. Though compared to Figures 16, 17, and 18, in which I illustrate $A_{1960,\widetilde{50}}$, $A_{1970,\widetilde{50}}$, and $A_{1980,\widetilde{50}}$ respectively, it is clear that the percentage of children who earn more income than their parents did has decreased generally over time, meanwhile, more variation is apparent throughout the United States for the 1980 birth cohort.

I reason that the differences in state economic performance play a role in the outcome of the child's income percentile rank, conditional on state-specific characteristics that may shape intergenerational mobility. Specifically, if during the childhood

Figure 15: Rate of Absolute Income Mobility, 1950 Birth Cohort

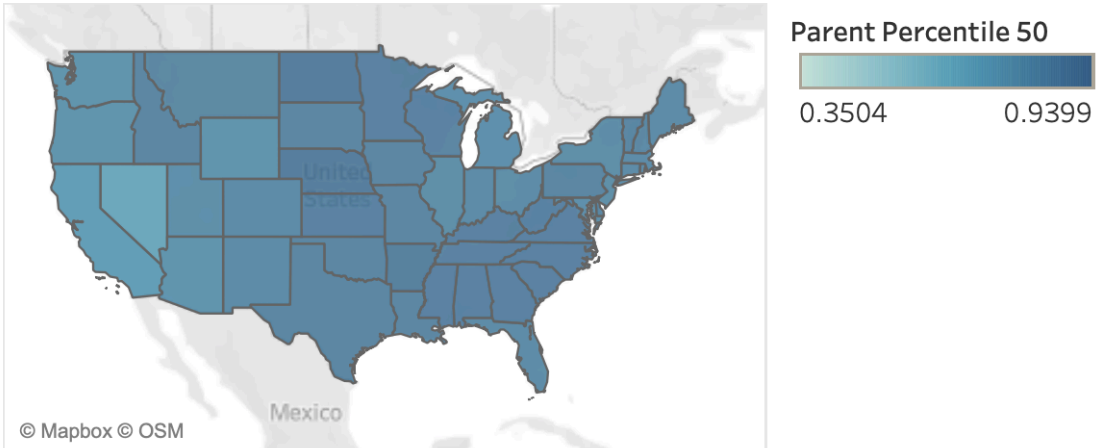


Figure 16: Rate of Absolute Income Mobility, 1960 Birth Cohort

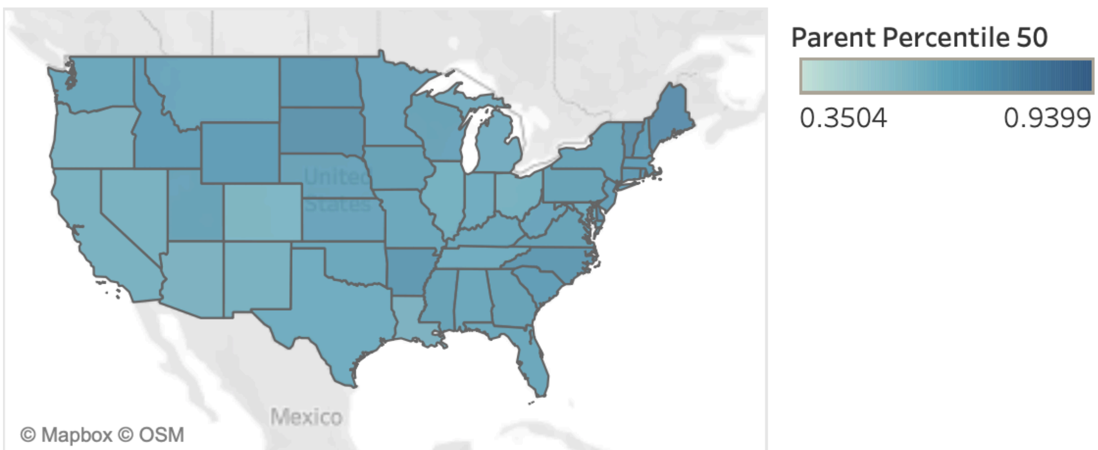


Figure 17: Rate of Absolute Income Mobility, 1970 Birth Cohort

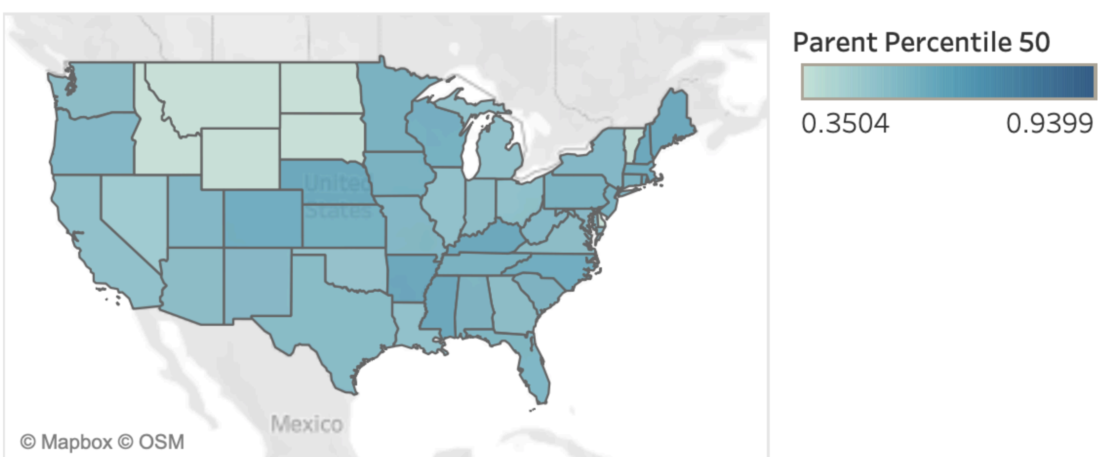
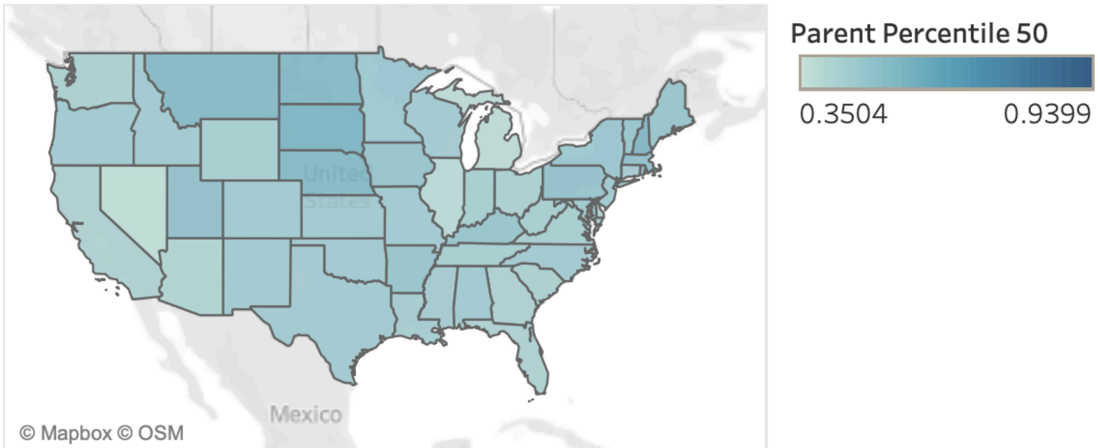


Figure 18: Rate of Absolute Income Mobility, 1980 Birth Cohort



of the 1950s birth cohort, California's economy as a whole outperforms Louisiana's economy (measured as the ratio of cyclical to trend components of state-level real total personal income), the children in California will have a better chance of earning a level of income that is above the level their parent earned, conditional on being born in California to parents in a particular income percentile rank.

I report the summary statistics of my data in Table 4. The independent variables, $\widetilde{c}_{i,t}$, represent the average business cycle experienced by families during the foundational years of the children. A negative $\widetilde{c}_{i,Y,10}$ and $\widetilde{c}_{i,Y,5}$ value represents a decrease in the cyclical component of real personal income as a percentage of trend; therefore, the negative minimum value in the average economic fluctuations represents a recession experienced by families. I exploit the heterogeneity of economic fluctuations experienced by four cohorts of children across each of the states, providing me with 200 separate experiences and therefore data points. In general, the mean of the rate of absolute income mobility, $A_{c,\widetilde{p}}$, at each parent percentile rank decreases as the parent percentile rank increases.

Table 4: Summary Statistics

Variables	(1) Min	(2) Max	(3) Mean	(4) St. Dev.	(5) Obs.
$\widetilde{c}_{i,Y,10}$	-0.882	0.669	-0.003	0.275	200
$\widetilde{c}_{i,Y,5}$	-2.628	1.867	0.215	0.557	200
$\widetilde{c}_{i,U,4}$	2.742	10.910	6.056	1.669	86
p_{crime}	746.8	6978.1	3569.0	1488.3	150
v_{crime}	24.3	1007.0	314.3	211.3	150
$A_{c,\widetilde{10}}$	0.079	0.929	0.783	0.094	191
$A_{c,\widetilde{20}}$	0.112	0.915	0.712	0.120	191
$A_{c,\widetilde{30}}$	0.126	0.892	0.676	0.131	191
$A_{c,\widetilde{40}}$	0.134	0.885	0.658	0.139	191
$A_{c,\widetilde{50}}$	0.138	0.879	0.638	0.142	191
$A_{c,\widetilde{60}}$	0.138	0.860	0.616	0.141	191
$A_{c,\widetilde{70}}$	0.142	0.842	0.591	0.144	191
$A_{c,\widetilde{80}}$	0.142	0.801	0.547	0.145	191
$A_{c,\widetilde{90}}$	0.141	0.728	0.472	0.142	191
$A_{c,\widetilde{100}}$	0.000	0.552	0.161	0.106	191

5.2 Panel Regressions and Estimates

I estimate specifications that take the general, minimalist form of Equation 40 (while accounting for state fixed effects in order to remove the variable bias that results from the heterogenous economic performance of each state), where $A_{c,\widetilde{p}}$ is the rate of absolute income mobility at percentile rank p for birth cohort c; $x_{i,t}$ is a vector of observable variables that vary across states (that is, i), across time (that is, t), or some combination of both states and time; ω is the coefficient on the continuous independent variable, $\widetilde{c}_{i,t}$—for example, the ten-year average over decade t of the state-i ratio of cyclical to trend components of real personal income—and u_i captures unobserved heterogeneity across states. I am primarily interested in the estimate of ω.

$$A_{\widetilde{p},c,i,t} = x_{i,t}\beta + \omega\widetilde{c}_{i,t} + u_i + v_{i,t} \tag{40}$$

In Tables 5 and 6, I report results for the ten-year average ratio of cyclical to trend components of real personal income. Based on my modeling, I expect the results to yield positive values for the coefficient ω, which in this case I label $\omega_{Y,10}$. Recall, $A_{\widetilde{p},c}$ is the rate of absolute income mobility for cohort c conditional on parental income percentile rank $\widetilde{p}$. Tables 5 and 6 include results for $\widetilde{p} = 10$, 20, 30, 40, and 50 and $\widetilde{p} = 60$, 70, 80, 90, and 100 respectively. The sign of the estimated coefficient for $\omega_{Y,10}$ is positive, as expected: the rate of absolute income mobility at income percentile rank $\widetilde{p}$ is positively correlated with average cyclical fluctuations in the economy in which the child lived sometime between the ages of 0 and 18, during which investments in the human capital of the child were presumably formative.

Table 5: Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,10}$	0.130***	0.191***	0.216***	0.226***	0.230***
	(0.0158)	(0.0203)	(0.0225)	(0.0248)	(0.0245)
Constant	0.786***	0.715***	0.678***	0.660***	0.640***
	(1.69e-05)	(2.17e-05)	(2.40e-05)	(2.64e-05)	(2.60e-05)
Observations	191	191	191	191	191
R-squared	0.238	0.227	0.227	0.216	0.212
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 5, I report that $\omega_{Y,10}$ is statistically significant (for $p < 0.01$) at each parent percentile rank, $\widetilde{p} = 10$, 20, 30, 40, and 50. Accounting for state fixed effects, $\omega_{Y,10}$ is 0.13 for a parental percentile rank of 10 ($\widetilde{p} = 10$). Therefore, one percentage-point positive cyclical fluctuation (as a percentage of trend) during the decade following the year indicating the cohort implies a 13 basis points increase in the probability a child will earn more income than their parent did. The impact of cyclical fluctuations increases as $\widetilde{p}$ increases, implying that an increase in economic fluctuations increase the rate of absolute income mobility more for the children born to parents in the middle range of income percentile ranks.

Table 6: Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,10}$	0.218***	0.227***	0.234***	0.230***	0.114***
	(0.0247)	(0.0242)	(0.0240)	(0.0263)	(0.0221)
Constant	0.617***	0.591***	0.547***	0.472***	0.159***
	(2.63e-05)	(2.57e-05)	(2.55e-05)	(2.80e-05)	(2.36e-05)
Observations	191	191	191	191	191
R-squared	0.198	0.209	0.218	0.227	0.155
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 6 I report results associated with parent percentile ranks, $\widetilde{p} = 60$, 70, 80, 90, and 100. Interestingly, the estimated coefficient of $\omega_{Y,10}$ is the highest for $\widetilde{p} = 80$, implying that a one percentage-point positive cyclical fluctuation (as a percentage of trend) increases by 23 basis points the probability a child born to a parent in the 80th income percentile will earn more income than their parent did. The R^2 in each case that I report in Tables 5 and 6 is about 0.2, implying that the percentage of variation explained by the model is low. This is not necessarily a problem; however, in order to account for any variation coming from the time series data, I add cohort fixed effects for the next set of panel regressions.

In the panel regressions associated with Tables 7 and 8, I include cohort (decade) dummies in order to capture statewide trends in the rate of absolute income mobility. Again, the results of these panel regressions, for which I expect the sign on the estimated value for $\omega_{Y,10}$ to be positive, include results for $p = 10$, 20, 30, 40, and 50 and $p = 60$, 70, 80, 90, and 100 respectively. The inclusion of cohort dummies seems most appropriate given the (downward) trend in intergenerational mobility.

Table 7: Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,10}$	0.00893	0.00784	0.0198	0.0213	0.0381**
	(0.0266)	(0.0182)	(0.0211)	(0.0199)	(0.0153)
1960.cohort	-0.0781***	-0.120***	-0.130***	-0.134***	-0.120***
	(0.0130)	(0.00986)	(0.0108)	(0.0105)	(0.00889)
1970.cohort	-0.0992***	-0.167***	-0.195***	-0.213***	-0.219***
	(0.00503)	(0.00567)	(0.00545)	(0.00585)	(0.00567)
1980.cohort	-0.176***	-0.276***	-0.307***	-0.329***	-0.329***
	(0.0112)	(0.00865)	(0.00975)	(0.00919)	(0.00812)
Constant	0.875***	0.856***	0.836***	0.829***	0.807***
	(0.00628)	(0.00502)	(0.00532)	(0.00531)	(0.00476)
Observations	191	191	191	191	191
R-squared	0.854	0.934	0.940	0.949	0.958
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 7, I report estimates of $\omega_{Y,10}$ that are smaller than those I reported earlier, and the estimate of $\omega_{Y,10}$ is statistically significant only for the case of $\widetilde{p} = 50$. Therefore, accounting for both state and cohort fixed effects, a one percentage-point positive cyclical fluctuation (as a percentage of trend) increases by about 4 basis points the rate of absolute income mobility conditional on a parental percentile rank equal to 50. The cohort dummies are in relation to the 1950 cohort; therefore the negative coefficient estimates are as I expect: the rate of absolute income mobility has decreased in relation to the 1950 birth cohort. Focusing on Table 8, the estimated coefficient for $\omega_{Y,10}$ is statistically significant conditional on $\widetilde{p} = 70$, 80, and 90.

Generally speaking, I interpret these results in Tables 7 and 8 to mean that cyclical fluctuations during childhood drive the rate of absolute income mobility conditional

Table 8: Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,10}$	0.0206	0.0368**	0.0385**	0.0405**	0.0228
	(0.0125)	(0.0176)	(0.0147)	(0.0178)	(0.0304)
1960.cohort	-0.127***	-0.124***	-0.135***	-0.141***	-0.0559***
	(0.00717)	(0.00990)	(0.0101)	(0.0133)	(0.0199)
1970.cohort	-0.219***	-0.224***	-0.230***	-0.227***	-0.0551***
	(0.00664)	(0.00782)	(0.00852)	(0.00963)	(0.0186)
1980.cohort	-0.332***	-0.327***	-0.328***	-0.310***	-0.119***
	(0.00704)	(0.00831)	(0.00939)	(0.0124)	(0.0211)
Constant	0.786***	0.760***	0.720***	0.640***	0.217***
	(0.00437)	(0.00575)	(0.00610)	(0.00797)	(0.0136)
Observations	191	191	191	191	191
R-squared	0.954	0.946	0.935	0.907	0.377
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

on parental income percentile ranks that are middling to high: specifically, $\widetilde{p} = 50$, 70, 80, and 90. Thus, in the context of my modeling, economic contractions bind the intertemporal budgets of middle to relatively high-income households. In each case, the estimated coefficient for $\omega_{Y,10}$ is roughly 0.04; thus, a one percentage-point positive cyclical fluctuation (as a percentage of trend) increases the child's rate of absolute income mobility by 4 basis points. The R^2 values are significantly higher when I include cohort dummies in the panel regression.

In Tables 5 through 8, I include every state in my analysis, resulting in an unbalanced panel because I do not have rates of absolute income mobility for a few states for some parental percentile ranks; for example, I do not have values for Alaska and Hawaii for the 1950 birth cohort because the cohort date precedes statehood in both cases. Therefore, in Tables 9 through 12, I drop the states with missing variables: namely Alaska, Delaware, Hawaii, Idaho, Montana, North Dakota, South Dakota, Vermont, and Wyoming. This creates a balanced panel of 41 states across 4 birth cohorts; therefore, the number of observations associated with this balanced panel is 164. I report results for the balanced panel regressions for $\widetilde{p} = 10$, 20, 30, 40, and 50 and $\widetilde{p} = 60$, 70, 80, 90, and 100 in Tables 9 and 10, respectively.

Table 9: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,10}$	0.146***	0.203***	0.231***	0.240***	0.239***
	(0.0166)	(0.0264)	(0.0294)	(0.0322)	(0.0332)
Constant	0.784***	0.712***	0.675***	0.656***	0.636***
	(0.000134)	(0.000214)	(0.000238)	(0.000261)	(0.000270)
Observations	164	164	164	164	164
R-squared	0.247	0.210	0.213	0.200	0.190
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 9, I report results that are similar to those I report earlier: $\omega_{Y,10}$ at each $\widetilde{p}$ is positive and statistically significant. My estimates of $\omega_{Y,10}$ for each $\widetilde{p}$ are slightly larger than those I obtain in my unbalanced panel regressions; for example, $A_{c,\widetilde{20}}$ increases by 1 basis point. Therefore, a one percentage-point positive cyclical fluctuation (as a percentage of trend) increases by 20 basis points the fraction of children earning more income than their parents did.

In Table 10, I report statistically significant estimates of $\omega_{Y,10}$ across all parental percentile ranks. For example, the estimate of $\omega_{Y,10}$, conditional on $\widetilde{p} = 90$, is 0.256, which implies that a one percentage-point positive cyclical fluctuation (as a percentage of trend) increases the child's rate of absolute income mobility by about 26 basis points. The estimate of $\omega_{Y,10}$ conditional on $\widetilde{p} = 100$ is (only) 0.11, implying that households in the top parental income percentile rank are less sensitive to cyclical

Table 10: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,10}$	0.237***	0.244***	0.250***	0.256***	0.110***
	(0.0327)	(0.0324)	(0.0324)	(0.0327)	(0.0232)
Constant	0.613***	0.588***	0.543***	0.467***	0.141***
	(0.000265)	(0.000263)	(0.000262)	(0.000265)	(0.000188)
Observations	164	164	164	164	164
R-squared	0.186	0.193	0.201	0.226	0.143
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

fluctuations (as a percentage of trend).

Table 11: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,10}$	0.00967	0.0117	0.0304**	0.0351**	0.0537***
	(0.0111)	(0.0163)	(0.0141)	(0.0131)	(0.0124)
1960.cohort	-0.0846***	-0.125***	-0.134***	-0.137***	-0.124***
	(0.00617)	(0.00935)	(0.00865)	(0.00876)	(0.00881)
1970.cohort	-0.0984***	-0.167***	-0.195***	-0.214***	-0.221***
	(0.00399)	(0.00531)	(0.00491)	(0.00528)	(0.00542)
1980.cohort	-0.183***	-0.279***	-0.311***	-0.332***	-0.330***
	(0.00719)	(0.00821)	(0.00757)	(0.00768)	(0.00777)
Constant	0.876***	0.857***	0.836***	0.828***	0.806***
	(0.00329)	(0.00463)	(0.00436)	(0.00463)	(0.00471)
Observations	164	164	164	164	164
R-squared	0.916	0.948	0.963	0.968	0.968
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Tables 11 and 12, I report results based on a balanced panel regression that includes both state and cohort fixed effects, conditional on $\widetilde{p} = 10$, 20, 30, 40, and 50 and $\widetilde{p} = 60$, 70, 80, 90, and 100, respectively. In Table 11, when I account for both state and cohort fixed effects in the balanced panel regression, the statistical significance holds for $\widetilde{p} = 30$, 40, and 50. Additionally, the value of $\omega_{Y,10}$ increases (relative to the corresponding unbalanced-panel result) for almost all parental percentile ranks. Nevertheless, the rate of absolute income mobility for children born to parents in $\widetilde{p} = 10$ and $\widetilde{p} = 20$ is not statistically significantly associated with cyclical fluctuations. I reason this is because an adverse aggregate shock, which tightens credit constraints, does not affect the amount a parent from the bottom income percentile invests in the human capital of their child; perhaps this is because the parents in the bottom income percentiles have less access to loans in the first place and therefore are not sensitive to economic fluctuations in the way my modeling proposes.

In Table 12, I report statistically significant results conditional on $\widetilde{p} = 60$, 70, 80, and 90. Specifically, the rate of absolute income mobility conditional on the parent percentile $\widetilde{p} = 70$ increases by 6.5 basis points due to a one percentage-point fluctuation in the business cycle. I reason that households in the parental percentile ranks of 60, 70, 80, and 90 have greater access to and rely relatively more on intermediated credit; therefore economic fluctuations affect the percentage of children who earn more than their parents in the medium- to high-income households. In this series of regressions, the R^2 is around 0.96, which implies that much of the variation is explained by this model.

In Tables 13 through 20, I report panel regressions for which my independent variable is the five-year (as opposed to the ten-year) average ratio of cyclical to trend components. I begin with the panel regressions for all states, accounting for state fixed effects. I expect the estimated value for $\omega_{Y,5}$ to be positive. I discuss my results for regression equations in which I include cohort dummies; thus, I discuss Tables 15

Table 12: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,10}$	0.0531***	0.0653***	0.0602***	0.0681***	-0.0137
	(0.0124)	(0.0167)	(0.0154)	(0.0218)	(0.0377)
1960.cohort	-0.124***	-0.126***	-0.140***	-0.150***	-0.0820***
	(0.00842)	(0.0107)	(0.0118)	(0.0171)	(0.0210)
1970.cohort	-0.223***	-0.230***	-0.236***	-0.233***	-0.0534***
	(0.00630)	(0.00731)	(0.00812)	(0.00936)	(0.0189)
1980.cohort	-0.330***	-0.328***	-0.330***	-0.309***	-0.120***
	(0.00698)	(0.00837)	(0.00940)	(0.0127)	(0.0218)
Constant	0.784***	0.760***	0.721***	0.641***	0.205***
	(0.00465)	(0.00585)	(0.00644)	(0.00907)	(0.0141)
Observations	164	164	164	164	164
R-squared	0.967	0.962	0.952	0.932	0.372
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

and 16 for the unbalanced panel regressions and Tables 19 and 20 for the balanced panel regressions for which I drop the same 9 states because of missing values (of the rate of absolute income mobility).

In Tables 15 and 16, I report no statistically significant estimates of the value for $\omega_{Y,5}$. It seems that the five-year average of the cyclical component (as a percentage of trend) fails to adequately capture business cyclicality because economic fluctuations may affect the rate of absolute income mobility with a lag. Specifically, the cyclical fluctuations early in the childhood may not tighten the credit constraints of a parent immediately. An alternative explanation for why I do not obtain statistically significant results using the five-year average is that in this case the children are between the ages of 0 and 13; therefore, the children are not of college attendance age, when skills formed may be particularly lucrative in increasing future economic outcomes.

Table 13: Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,5}$	-0.0291**	-0.0374*	-0.0446**	-0.0484**	-0.0475**
	(0.0117)	(0.0191)	(0.0214)	(0.0227)	(0.0235)
Constant	0.794***	0.725***	0.690***	0.673***	0.653***
	(0.00312)	(0.00510)	(0.00574)	(0.00607)	(0.00628)
Observations	191	191	191	191	191
R-squared	0.027	0.020	0.022	0.022	0.020
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,5}$	-0.0451*	-0.0422*	-0.0349	-0.0340	-0.0162
	(0.0228)	(0.0228)	(0.0239)	(0.0225)	(0.0131)
Constant	0.628***	0.602***	0.556***	0.480***	0.163***
	(0.00610)	(0.00611)	(0.00640)	(0.00602)	(0.00351)
Observations	191	191	191	191	191
R-squared	0.019	0.016	0.011	0.011	0.007
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

My results for the corresponding balanced-panel regressions, which I report in Tables 19 through 20, are substantially identical to my unbalanced-panel results in this case.

In Tables 21 through 24, I report results of (only) balanced panel regressions for which my independent variable is the average unemployment rate, which is cyclical in nature. The state-level unemployment rate is available back to the year 1976. Therefore, I am not able to use every birth cohort. Instead, I focus on the 1970

Table 15: Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,5}$	-0.00790	-0.00201	-0.00758	-0.00624	0.00208
	(0.00879)	(0.00804)	(0.00823)	(0.00754)	(0.00613)
1960.cohort	-0.0851***	-0.124***	-0.142***	-0.145***	-0.135***
	(0.00627)	(0.00700)	(0.00791)	(0.00754)	(0.00759)
1970.cohort	-0.102***	-0.168***	-0.199***	-0.216***	-0.221***
	(0.00623)	(0.00623)	(0.00702)	(0.00695)	(0.00683)
1980.cohort	-0.178***	-0.278***	-0.314***	-0.337***	-0.345***
	(0.00673)	(0.00609)	(0.00688)	(0.00708)	(0.00651)
Constant	0.880***	0.859***	0.844***	0.836***	0.815***
	(0.00460)	(0.00484)	(0.00553)	(0.00510)	(0.00511)
Observations	191	191	191	191	191
R-squared	0.855	0.934	0.939	0.948	0.955
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

and 1980 birth cohorts. In this case, I average the unemployment rate for the years 1976 through 1979 for the 1970 birth cohort. And I average the unemployment rate for the years 1986 through 1989 for the 1980 birth cohort. I expect the estimate of the value of $\omega_{U,4}$ to be negative because the unemployment rate is countercyclical. My balanced panel excludes states for which values of the rate of absolute income mobility for the 1970 birth cohort are missing: namely, Delaware, Idaho, Montana, North Dakota, South Dakota, Vermont, and Wyoming. In Tables 23 and 24, in which I report results of regressions that include both state and cohort fixed effects, the estimated values of $\omega_{U,4}$ are negative, as expected, conditional on $\widetilde{p} = 40$, 50, 60, and 100. Nevertheless, none of these results are statistically significant.

Next, I report results for which my regression equation includes the explanatory variables for property and violent crimes. In tables 25 and 26, I regress the rate of absolute mobility on real personal income averaged over 10 years, $\widetilde{c}_{i,Y,10}$, while

Table 16: Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,5}$	0.00262	0.00339	0.00568	-0.00932	0.00141
	(0.00823)	(0.00878)	(0.00840)	(0.0117)	(0.0111)
1960.cohort	-0.135***	-0.138***	-0.149***	-0.162***	-0.0650***
	(0.00829)	(0.00924)	(0.00956)	(0.0121)	(0.0148)
1970.cohort	-0.220***	-0.226***	-0.231***	-0.233***	-0.0563***
	(0.00790)	(0.00900)	(0.00948)	(0.0107)	(0.0187)
1980.cohort	-0.340***	-0.343***	-0.345***	-0.325***	-0.128***
	(0.00759)	(0.00837)	(0.00873)	(0.00984)	(0.0165)
Constant	0.790***	0.767***	0.726***	0.654***	0.222***
	(0.00624)	(0.00676)	(0.00677)	(0.00817)	(0.0121)
Observations	191	191	191	191	191
R-squared	0.953	0.943	0.932	0.905	0.374
Number of state_code	50	50	50	50	50
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,5}$	-0.0419***	-0.0586***	-0.0670***	-0.0706***	-0.0689**
	(0.0131)	(0.0199)	(0.0227)	(0.0244)	(0.0255)
Constant	0.797***	0.731***	0.696***	0.678***	0.657***
	(0.00370)	(0.00559)	(0.00640)	(0.00685)	(0.00719)
Observations	164	164	164	164	164
R-squared	0.051	0.043	0.044	0.043	0.039
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

accounting for property and crime rates (per 100,000 individuals), p_{crime} and v_{crime}. Unfortunately, because the crime rate data begin in 1960, I must drop the 1950 birth

Table 18: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,5}$	-0.0667**	-0.0626**	-0.0539**	-0.0410	-0.0130
	(0.0254)	(0.0252)	(0.0264)	(0.0265)	(0.0117)
Constant	0.634***	0.607***	0.560***	0.480***	0.145***
	(0.00714)	(0.00710)	(0.00744)	(0.00745)	(0.00329)
Observations	164	164	164	164	164
R-squared	0.037	0.031	0.023	0.014	0.005
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,5}$	-0.00132	0.000992	-0.00332	0.000877	0.00700
	(0.00919)	(0.00876)	(0.00758)	(0.00636)	(0.00602)
1960.cohort	-0.0892***	-0.129***	-0.148***	-0.151***	-0.145***
	(0.00537)	(0.00641)	(0.00690)	(0.00662)	(0.00706)
1970.cohort	-0.0992***	-0.167***	-0.198***	-0.215***	-0.222***
	(0.00447)	(0.00540)	(0.00564)	(0.00592)	(0.00651)
1980.cohort	-0.186***	-0.283***	-0.321***	-0.345***	-0.351***
	(0.00576)	(0.00606)	(0.00623)	(0.00609)	(0.00668)
Constant	0.879***	0.859***	0.844***	0.835***	0.815***
	(0.00387)	(0.00438)	(0.00434)	(0.00435)	(0.00491)
Observations	164	164	164	164	164
R-squared	0.916	0.947	0.961	0.966	0.965
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

cohort data. Once again, I expect the relationship between real personal income and the rate of absolute mobility to be positive.

Table 20: Balanced Panel Regressions of State-Level Mobility and Real Personal Income, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,5}$	0.00967	0.00901	0.0107	0.00455	0.00940
	(0.00593)	(0.00760)	(0.00775)	(0.0101)	(0.0119)
1960.cohort	-0.143***	-0.150***	-0.162***	-0.177***	-0.0727***
	(0.00738)	(0.00825)	(0.00884)	(0.0114)	(0.0155)
1970.cohort	-0.223***	-0.230***	-0.235***	-0.234***	-0.0500**
	(0.00738)	(0.00897)	(0.00946)	(0.0103)	(0.0194)
1980.cohort	-0.351***	-0.353***	-0.354***	-0.335***	-0.117***
	(0.00664)	(0.00740)	(0.00773)	(0.00971)	(0.0162)
Constant	0.792***	0.771***	0.729***	0.654***	0.199***
	(0.00531)	(0.00623)	(0.00634)	(0.00766)	(0.0125)
Observations	164	164	164	164	164
R-squared	0.964	0.957	0.948	0.926	0.372
Number of state_code	41	41	41	41	41
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Balanced Panel Regressions of State-Level Mobility and Unemployment Rate, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{U,4}$	0.00684	0.00893	0.00903	0.00825	0.00763
	(0.00626)	(0.00844)	(0.00880)	(0.00888)	(0.00876)
Constant	0.689***	0.574***	0.523***	0.500***	0.480***
	(0.0387)	(0.0522)	(0.0544)	(0.0549)	(0.0542)
Observations	86	86	86	86	86
R-squared	0.023	0.024	0.022	0.017	0.015
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Tables 25 and 26, I report a positive relationship between mobility and economic fluctuations. Much of the statistical significance (that I report in Tables 11 and 12 for

Table 22: Balanced Panel Regressions of State-Level Mobility and Unemployment Rate, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{U,4}$	0.00835	0.00920	0.0124	0.0109	0.00129
	(0.00876)	(0.00865)	(0.00773)	(0.00660)	(0.00473)
Constant	0.452***	0.419***	0.356***	0.297***	0.110***
	(0.0541)	(0.0535)	(0.0478)	(0.0408)	(0.0292)
Observations	86	86	86	86	86
R-squared	0.019	0.025	0.048	0.049	0.001
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	No	No	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Balanced Panel Regressions of State-Level Mobility and Unemployment Rate, $10 \leq \widetilde{p} \leq 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{U,4}$	0.00101	0.000870	0.000418	-0.000767	-0.00123
	(0.00460)	(0.00387)	(0.00343)	(0.00329)	(0.00300)
1980.cohort	-0.0813***	-0.113***	-0.120***	-0.126***	-0.124***
	(0.00645)	(0.00621)	(0.00523)	(0.00518)	(0.00538)
Constant	0.766***	0.680***	0.637***	0.619***	0.596***
	(0.0274)	(0.0235)	(0.0211)	(0.0199)	(0.0197)
Observations	86	86	86	86	86
R-squared	0.764	0.878	0.922	0.927	0.934
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

example) does not hold when I include the explanatory crime rate variables. Though, I do not attribute the loss of statistical significance to the addition of the explanatory crime rate variables; instead, I attribute the loss of significance to the loss of the 1950 birth cohort. The limited time frame of the property and violent crime rates decreases

Table 24: Balanced Panel Regressions of State-Level Mobility and Unemployment Rate, $60 \leq \widetilde{p} \leq 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{U,4}$	-0.000314	0.000811	0.00455	0.00425	-0.00307
	(0.00268)	(0.00249)	(0.00274)	(0.00265)	(0.00459)
1980.cohort	-0.121***	-0.117***	-0.110***	-0.0933***	-0.0609***
	(0.00487)	(0.00438)	(0.00551)	(0.00607)	(0.00870)
Constant	0.566***	0.529***	0.460***	0.385***	0.168***
	(0.0173)	(0.0159)	(0.0168)	(0.0170)	(0.0293)
Observations	86	86	86	86	86
R-squared	0.941	0.947	0.904	0.858	0.543
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the number of observations in the regression. In summary, the panel regression results for the relationship between the rate of absolute income mobility and the ten-year average cyclical component (as a share of trend), conditional on state and cohort dummies, yields the most definitive and interesting results.

5.3 Implications, Limitations, and Areas for Future Research

A positive fluctuation in the business cycle increases the percentage chance of a child achieving the American Dream (by earning an income higher than the income their parents earned) conditional on the parental income percentile rank. That these effects pertain to middle and relatively high-income households is interesting, particularly if, as I argue, the availability of credit underlies the transmission mechanism from cyclical fluctuations to economic mobility. One implication of my research is that middle- and high-income households rely on credit to finance investment in human capital to an extent that relatively low-income households do not.

Another implication of my research is the importance of stabilization policies that

Table 25: Panel Regressions of State-Level Mobility on Real Personal Income and Crime, $10 \le \widetilde{p} \le 50$

VARIABLES	(1) $A_{c,\widetilde{10}}$	(2) $A_{c,\widetilde{20}}$	(3) $A_{c,\widetilde{30}}$	(4) $A_{c,\widetilde{40}}$	(5) $A_{c,\widetilde{50}}$
$\omega_{Y,10}$	0.0399	0.0293	0.0344	0.0280	0.0431**
	(0.0334)	(0.0228)	(0.0282)	(0.0281)	(0.0198)
p_{crime}	-1.72e-06	-6.33e-06	-8.03e-07	-3.17e-06	-7.03e-06
	(1.04e-05)	(1.30e-05)	(1.25e-05)	(1.31e-05)	(1.15e-05)
v_{crime}	-1.55e-05	1.14e-05	3.14e-06	-1.19e-05	-2.45e-05
	(5.55e-05)	(5.87e-05)	(5.16e-05)	(4.74e-05)	(5.11e-05)
1970.cohort	-0.0244	-0.0433*	-0.0680***	-0.0705***	-0.0780***
	(0.0206)	(0.0242)	(0.0218)	(0.0242)	(0.0204)
1980.cohort	-0.0905***	-0.144***	-0.177***	-0.184***	-0.181***
	(0.0285)	(0.0291)	(0.0300)	(0.0330)	(0.0278)
Constant	0.803***	0.746***	0.704***	0.698***	0.698***
	(0.0280)	(0.0293)	(0.0304)	(0.0316)	(0.0266)
Observations	129	129	129	129	129
R-squared	0.752	0.871	0.900	0.916	0.934
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Panel Regressions of State-Level Mobility on Real Personal Income and Crime, $60 \le \widetilde{p} \le 100$

VARIABLES	(1) $A_{c,\widetilde{60}}$	(2) $A_{c,\widetilde{70}}$	(3) $A_{c,\widetilde{80}}$	(4) $A_{c,\widetilde{90}}$	(5) $A_{c,\widetilde{100}}$
$\omega_{Y,10}$	0.0179	0.0342	0.0308	0.0316*	0.0240
	(0.0129)	(0.0232)	(0.0208)	(0.0167)	(0.0207)
p_{crime}	1.05e-06	8.87e-06	1.80e-05	7.38e-06	1.28e-05
	(9.57e-06)	(1.00e-05)	(1.08e-05)	(1.04e-05)	(1.55e-05)
v_{crime}	1.47e-05	-3.99e-05	-5.41e-05	-8.01e-06	6.96e-06
	(4.32e-05)	(5.02e-05)	(4.70e-05)	(5.94e-05)	(9.37e-05)
1970.cohort	-0.0923***	-0.103***	-0.110***	-0.0856***	-0.0157
	(0.0181)	(0.0200)	(0.0204)	(0.0191)	(0.0332)
1980.cohort	-0.210***	-0.210***	-0.216***	-0.173***	-0.0761*
	(0.0230)	(0.0265)	(0.0273)	(0.0252)	(0.0443)
Constant	0.643***	0.610***	0.540***	0.465***	0.105***
	(0.0213)	(0.0253)	(0.0248)	(0.0216)	(0.0310)
Observations	129	129	129	129	129
R-squared	0.944	0.934	0.911	0.853	0.306
Number of state_code	43	43	43	43	43
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

help reduce the impact of an economic shock. A negative economic shock causes a multitude of effects; my research emphasizes the decrease in the rate of absolute mobility when the negative economic shock occurs in the early years of a child's life. During recessions, the decrease in any component of aggregate demand lowers the price level and the amount of output and so too an individual's level of savings. Therefore, a parent who relies on borrowing to invest in the human capital of their child is unable to secure loans, limiting the child's ability to earn income. In order to maintain the health of the economy, economists implement stabilization policies that lessen the effect of negative economic shocks and maintain the ease of access to credit.

There are several types of economic policy that reduce the effects of negative aggregate shocks. Expansionary fiscal policy directly affects aggregate demand by increasing government spending and cutting taxes. Each of these options potentially increases output and, therefore, savings. Monetary policy indirectly affects aggregate demand through the interest rate. The Federal Reserve System controls the money supply and interest rates. The Federal Reserve System implements expansionary monetary policy by increasing the money supply, perhaps by purchasing Treasury bonds, resulting in a decrease in the level of interest rates. Relatively low interest rates stimulate investments (perhaps in human capital) and household consumption. Each of these channels reduces the severity of negative economic shocks and maintains households' access to credit. Therefore, stabilization policies that help maintain a stable economy also help maintain investment in the human capital of children, thereby maintaining their rates of absolute income mobility.

Some limitations of my research include the type of data available, my de-trending method, how I adjust for inflation, and potential endogeneity problems. The first limitation of my research is the lack of available state-level data. Real GDP is the most common economic variable used to evaluate fluctuations of the real economy.

Therefore, the ideal state-level measure is real GSP, which is analogous to real GDP. Unfortunately, real GSP is not available during the time frame I am interested in at a quarterly frequency, so I use real personal income. A second limitation is that I use the HP-filter to recover the cyclical and trend components of real personal income; this is one of several de-trending methods. While the HP-filter is conventional, it is simply a smoothing algorithm that does not account for the fundamental forces driving the trend component. Other de-trending methods may yield different results in my panel regressions. Additionally, I use the national consumer price index to adjust for inflation in each state. Although this is a reasonable way to account for changes in the price level, state-level measures of the consumer price index may provide different results. And finally, I use conventional panel regression for a dataset that includes many more states than it does time periods. Thus, a dynamic panel regression technique may be appropriate.

That economic fluctuations drive the rate of absolute mobility suggests one area for future research is how state-level economic stabilization policy might affect state-level economic fluctuations and, thus, maintain a healthy state-level economy. A second area for future research is the role of state- and local-government investment in the human capital of children. Understanding the ways state and local governments can best invest in the human capital of children would provide additional insight into how a child's ability to earn income is determined. Finally, a third area for future research is how state-level variation in usury laws shape the availability of credit across states.

6 Conclusion

In this thesis, I test my central hypothesis that aggregate economic fluctuations—business cycles—shape intergenerational economic mobility. I argue that these cycles create countercyclical credit constraints for households that rely on credit to invest in the human capital of their children. Thus, these constraints effectively limit the foundational skills and expected earnings of the child. My working measure of intergenerational mobility is the rate of absolute income mobility, which measures the fraction of adult children who earn more than their parents earned, conditional on the parent's income rank in their income distribution. According to Chetty et al. (2017, p.1), earning more than our parents did is "one of the defining features of the American Dream."

To test my hypothesis, I exploit heterogenous state-level economic fluctuations. I show that aggregate economic shocks do not flow through the economy uniformly. In fact, short-run fluctuations measured by gross state product, real personal income, and the unemployment rate, vary across states in terms of timing, amplitude, and duration. I use this variation, along with variation in state-level rates of absolute income mobility of children in 1950, 1960, 1970, and 1980 birth cohorts, to construct a panel dataset. Thus, for my panel regressions, I pair a state-level estimate of the rate of absolute income mobility for a particular birth cohort—the dependent variable—with a state-level measure of the business cycle during the decade following the cohort year, when children in the birth cohort are heavily dependent on their parents.

Overall, I find that variation in state-level business cycles measured as the ten-year average cyclical component (as a share of trend) of state-level real personal income yield the most precise and interesting results: average cyclical fluctuations in the economy in which children lived between the ages of 0 and 18 drive to some extent their average rate of absolute income mobility through adulthood. My results are statistically significant in the cases where parental income percentile ranks equal 50, 70, 80, and 90.

I conclude that aggregate fluctuations drive rates of absolute mobility for middle- to high-income households. One possible implication of these results is that households that rely most on credit markets to fund investment in the human capital of their child rank in middle- to high-income percentiles. Put differently, credit-rationing constrains only households that can access credit in the first place. I also measure the state-level business cycle as the five-year average cyclical component (as a share of trend) of state-level real personal income and as the average unemployment rate, both during the child's formative early years. In these cases, my results are not statistically significant.

The positive relationship between business cycles (during childhood) and American dreams (during adulthood) implies the importance of household access to capital and, thus, macroeconomic stabilization policies that maintain a well-functioning economy, complete with an ample supply of credit. Moreover, given the heterogeneity of state-level aggregate economic outcomes that I demonstrate, macroeconomic stabilization policies tailored to state-level economic circumstances seem appropriate. My results broadly support state-level automatic stabilizers—in the form of direct stimulus payments to households, say—triggered by a state-level recession indicator, such as an appropriately modified Sahm rule for example.

7 References

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Table A1: Correlations, Real GSP, Cyclical Components

	US	AL	AK	AZ	AR	CA	CO	CT	DE	DC	FL	GA	HI	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
US	1.0																																																			
AL	0.8	1.0																																																		
AK	-0.2	-0.2	1.0																																																	
AZ	0.9	0.8	-0.1	1.0																																																
AR	0.7	0.8	-0.3	0.6	1.0																																															
CA	0.9	0.6	-0.3	0.8	0.6	1.0																																														
CO	0.7	0.4	-0.2	0.6	0.4	0.8	1.0																																													
CT	0.8	0.6	-0.0	0.7	0.2	0.7	0.6	1.0																																												
DE	0.2	0.1	0.1	0.1	0.1	0.2	0.1	0.1	1.0																																											
DC	0.1	0.2	-0.3	0.1	0.1	0.1	0.2	0.1	-0.0	1.0																																										
FL	0.9	0.7	-0.2	0.9	0.6	0.8	0.7	0.7	0.2	-0.0	1.0																																									
GA	0.9	0.7	-0.3	0.8	0.6	0.8	0.6	0.6	0.3	0.2	0.9	1.0																																								
HI	0.8	0.8	-0.2	0.8	0.6	0.7	0.5	0.7	0.1	0.3	0.8	0.8	1.0																																							
ID	0.7	0.6	-0.3	0.7	0.5	0.8	0.8	0.7	-0.0	0.1	0.7	0.7	0.6	1.0																																						
IL	0.9	0.8	-0.1	0.9	0.7	0.7	0.5	0.6	0.3	0.0	0.8	0.8	0.7	0.5	1.0																																					
IN	0.8	0.8	-0.5	0.8	0.7	0.7	0.6	0.6	0.0	0.3	0.8	0.8	0.7	0.7	0.8	1.0																																				
IA	0.8	0.5	-0.1	0.6	0.4	0.5	0.6	0.6	0.4	0.1	0.7	0.7	0.5	0.4	0.8	0.7	1.0																																			
KS	0.7	0.6	-0.2	0.7	0.4	0.7	0.7	0.7	0.1	0.3	0.7	0.7	0.7	0.7	0.7	0.7	0.6	1.0																																		
KY	0.8	0.9	-0.3	0.7	0.8	0.6	0.4	0.5	0.1	0.2	0.7	0.7	0.8	0.5	0.8	0.8	0.5	0.6	1.0																																	
LA	-0.2	-0.2	0.1	-0.4	-0.1	-0.3	-0.2	-0.3	0.2	0.2	-0.3	-0.3	-0.3	-0.2	-0.2	-0.1	-0.0	-0.3	-0.1	1.0																																
ME	0.5	0.5	-0.2	0.4	0.4	0.3	0.3	0.4	0.2	0.3	0.5	0.5	0.5	0.4	0.4	0.6	0.4	0.5	0.5	0.4	1.0																															
MD	0.3	0.5	-0.3	0.3	0.4	0.1	-0.1	0.1	0.2	0.4	0.4	0.5	0.5	0.2	0.4	0.4	0.2	0.3	0.6	0.1	0.6	1.0																														
MA	0.7	0.7	-0.1	0.6	0.5	0.5	0.4	0.6	0.3	0.5	0.6	0.7	0.7	0.4	0.7	0.6	0.6	0.6	0.7	0.0	0.5	0.6	1.0																													
MI	0.8	0.8	-0.3	0.8	0.7	0.5	0.3	0.5	0.1	0.2	0.7	0.8	0.8	0.4	0.8	0.8	0.6	0.5	0.8	-0.2	0.4	0.5	0.7	1.0																												
MN	0.7	0.7	-0.5	0.6	0.7	0.6	0.5	0.3	0.1	0.3	0.6	0.7	0.6	0.6	0.6	0.8	0.5	0.6	0.8	-0.1	0.4	0.5	0.6	0.7	1.0																											
MS	0.6	0.6	-0.2	0.6	0.5	0.7	0.7	0.6	-0.0	0.3	0.5	0.5	0.6	0.7	0.4	0.6	0.4	0.7	0.5	-0.1	0.4	0.1	0.4	0.3	0.5	1.0																										
MO	0.4	0.4	-0.1	0.2	0.4	0.4	0.5	0.3	-0.0	0.3	0.2	0.1	0.3	0.5	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.0	0.3	0.1	0.4	0.6	1.0																									
MT	0.8	0.7	-0.0	0.7	0.5	0.7	0.6	0.7	0.4	0.2	0.7	0.7	0.6	0.5	0.8	0.6	0.7	0.6	0.5	-0.2	0.3	0.2	0.6	0.6	0.4	0.5	0.3	1.0																								
NE	0.5	0.6	-0.4	0.5	0.6	0.4	0.2	0.3	0.3	0.1	0.5	0.6	0.5	0.3	0.6	0.6	0.4	0.4	0.7	-0.1	0.4	0.5	0.6	0.6	0.5	0.1	0.0	0.5	1.0																							
NV	0.9	0.8	-0.1	0.9	0.7	0.8	0.6	0.7	0.2	0.1	0.9	0.9	0.9	0.7	0.8	0.7	0.5	0.7	0.8	-0.3	0.5	0.5	0.7	0.8	0.6	0.5	0.2	0.7	0.6	1.0																						
NH	0.6	0.6	-0.1	0.5	0.4	0.3	0.2	0.5	0.1	-0.1	0.6	0.5	0.5	0.2	0.6	0.5	0.5	0.3	0.6	0.0	0.5	0.5	0.6	0.6	0.3	0.1	0.1	0.4	0.5	0.6	1.0																					
NJ	0.8	0.7	-0.2	0.7	0.5	0.7	0.7	0.8	0.0	0.2	0.7	0.7	0.8	0.8	0.7	0.7	0.6	0.7	0.7	-0.2	0.5	0.2	0.6	0.5	0.6	0.8	0.6	0.7	0.3	0.7	0.4	1.0																				
NM	0.1	-0.0	0.6	-0.0	0.0	0.0	0.3	0.0	0.5	0.0	0.1	-0.0	-0.1	0.0	0.1	-0.1	0.3	0.2	-0.1	0.4	0.1	-0.1	0.1	-0.1	-0.1	0.0	0.3	0.2	-0.2	0.1	0.0	0.0	1.0																			
NY	0.1	-0.0	0.1	-0.1	-0.2	-0.1	-0.4	0.1	0.3	-0.2	0.1	0.0	-0.1	-0.3	0.2	-0.0	0.2	-0.2	0.1	0.3	0.2	0.2	0.1	0.2	-0.2	-0.4	-0.2	0.0	0.2	-0.1	0.4	-0.1	-0.1	1.0																		
NC	0.8	0.6	-0.3	0.7	0.5	0.8	0.6	0.7	0.2	0.1	0.8	0.7	0.7	0.8	0.7	0.7	0.5	0.7	0.6	-0.2	0.5	0.3	0.5	0.5	0.6	0.6	0.4	0.6	0.4	0.8	0.4	0.8	0.1	-0.0	1.0																	
ND	0.3	0.3	0.2	0.2	0.3	0.1	0.1	0.0	0.1	-0.1	0.0	0.0	0.1	-0.1	0.4	0.2	0.4	0.0	0.3	-0.0	-0.2	-0.2	0.2	0.3	0.3	0.2	0.3	0.3	-0.0	0.0	0.0	0.3	0.1	0.1	-0.0	1.0																
OH	0.8	0.8	-0.4	0.7	0.7	0.7	0.6	0.5	0.3	0.3	0.7	0.8	0.7	0.6	0.8	0.8	0.7	0.7	0.8	-0.2	0.4	0.4	0.7	0.8	0.8	0.5	0.3	0.7	0.7	0.7	0.4	0.6	0.0	-0.1	0.6	0.4	1.0															
OK	0.4	0.3	0.2	0.3	0.3	0.5	0.6	0.3	0.3	-0.0	0.3	0.2	0.2	0.4	0.4	0.2	0.4	0.4	0.2	-0.0	-0.1	-0.3	0.2	0.1	0.2	0.4	0.5	0.4	-0.0	0.3	-0.0	0.4	0.6	-0.2	0.4	0.5	0.4	1.0														
OR	0.7	0.6	-0.1	0.8	0.5	0.8	0.7	0.7	0.2	0.3	0.8	0.8	0.8	0.8	0.6	0.6	0.5	0.8	0.5	-0.3	0.5	0.4	0.6	0.5	0.4	0.7	0.2	0.6	0.4	0.8	0.3	0.7	0.1	-0.2	0.8	-0.1	0.6	0.3	1.0													
PA	0.8	0.7	-0.4	0.7	0.6	0.6	0.7	0.6	0.1	0.5	0.6	0.7	0.7	0.7	0.7	0.8	0.7	0.7	0.7	-0.1	0.4	0.3	0.7	0.6	0.7	0.7	0.6	0.7	0.4	0.6	0.4	0.8	0.1	-0.2	0.6	0.3	0.8	0.4	0.6	1.0												
RI	0.4	0.4	0.1	0.3	0.4	0.1	-0.1	0.2	0.4	-0.3	0.4	0.3	0.3	0.0	0.5	0.3	0.3	0.0	0.5	0.2	0.3	0.4	0.3	0.5	0.2	-0.1	0.0	0.3	0.4	0.4	0.6	0.2	0.2	0.5	0.3	0.1	0.3	-0.0	0.1	0.1	1.0											
SC	0.9	0.8	-0.3	0.9	0.6	0.8	0.7	0.7	0.1	0.3	0.9	0.9	0.8	0.8	0.8	0.8	0.7	0.8	0.7	-0.4	0.5	0.4	0.7	0.7	0.7	0.7	0.3	0.7	0.6	0.9	0.4	0.8	-0.0	-0.2	0.8	0.1	0.8	0.3	0.8	0.8	0.1	1.0										
SD	0.3	0.4	-0.1	0.3	0.2	0.1	0.2	0.3	0.1	0.3	0.2	0.3	0.4	0.1	0.3	0.2	0.3	0.5	0.3	-0.4	0.1	0.2	0.4	0.3	0.3	0.3	-0.1	0.3	0.4	0.3	0.1	0.3	-0.1	-0.2	0.3	0.1	0.4	0.1	0.3	0.4	-0.1	0.4	1.0									
TN	0.8	0.8	-0.1	0.8	0.7	0.7	0.4	0.5	0.2	0.1	0.7	0.7	0.8	0.5	0.7	0.6	0.5	0.6	0.8	-0.3	0.3	0.4	0.6	0.7	0.6	0.6	0.3	0.6	0.5	0.7	0.4	0.8	-0.0	-0.1	0.6	0.4	0.7	0.4	0.7	0.6	0.3	0.7	0.4	1.0								
TX	0.7	0.5	0.2	0.7	0.4	0.7	0.6	0.6	0.2	-0.2	0.7	0.5	0.5	0.5	0.7	0.5	0.6	0.5	0.4	-0.3	0.0	-0.2	0.3	0.5	0.3	0.4	0.4	0.8	0.2	0.6	0.3	0.6	0.4	-0.1	0.5	0.4	0.5	0.7	0.5	0.5	0.3	0.6	0.1	0.5	1.0							
UT	0.8	0.7	-0.0	0.9	0.5	0.8	0.6	0.7	0.2	-0.1	0.9	0.8	0.7	0.7	0.8	0.6	0.5	0.7	0.6	-0.4	0.4	0.3	0.5	0.6	0.4	0.5	0.1	0.7	0.5	0.9	0.5	0.6	0.1	-0.1	0.8	-0.1	0.6	0.3	0.8	0.5	0.3	0.8	0.2	0.6	0.7	1.0						
VT	0.3	0.5	-0.1	0.2	0.4	0.0	-0.1	0.1	0.2	0.5	0.1	0.3	0.5	0.0	0.3	0.3	0.2	0.3	0.6	0.2	0.5	0.7	0.7	0.5	0.4	0.2	0.3	0.2	0.4	0.3	0.4	0.3	0.1	0.1	0.2	0.1	0.4	0.0	0.3	0.4	0.3	0.3	0.4	0.5	-0.1	0.1	1.0					
VA	0.6	0.7	-0.0	0.5	0.5	0.3	0.1	0.3	0.2	0.2	0.5	0.5	0.6	0.2	0.6	0.5	0.4	0.3	0.7	0.1	0.5	0.6	0.7	0.6	0.4	0.1	0.3	0.5	0.6	0.6	0.6	0.4	0.1	0.4	0.4	0.1	0.4	0.0	0.3	0.4	0.6	0.4	0.2	0.5	0.2	0.4	0.6	1.0				
WA	0.8	0.7	-0.1	0.8	0.5	0.8	0.8	0.8	0.0	0.2	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.5	-0.3	0.5	0.1	0.6	0.5	0.5	0.8	0.5	0.7	0.3	0.7	0.3	0.8	0.1	-0.2	0.7	0.2	0.6	0.4	0.7	0.7	-0.0	0.8	0.2	0.6	0.7	0.7	0.1	0.4	1.0			
WV	0.2	0.4	0.2	0.2	0.5	0.1	0.1	-0.1	0.0	0.2	0.0	0.0	0.2	0.2	0.2	0.2	-0.0	0.2	0.3	0.2	0.1	0.1	0.2	0.2	0.3	0.3	0.5	0.2	0.0	0.2	0.0	0.1	0.3	-0.4	0.1	0.3	0.3	0.4	0.1	0.3	0.0	0.1	0.1	0.2	0.2	0.0	0.3	0.3	0.2	1.0		
WI	0.9	0.8	-0.3	0.8	0.7	0.6	0.5	0.5	0.3	0.2	0.8	0.8	0.7	0.5	0.9	0.8	0.7	0.7	0.8	-0.1	0.5	0.6	0.8	0.9	0.7	0.4	0.2	0.7	0.6	0.8	0.6	0.6	0.1	0.2	0.7	0.3	0.8	0.3	0.6	0.7	0.5	0.8	0.3	0.7	0.5	0.7	0.5	0.7	0.6	0.2	1.0	
WY	0.3	0.1	0.4	0.3	0.1	0.5	0.6	0.4	0.1	-0.0	0.3	0.1	0.2	0.5	0.2	0.1	0.1	0.4	-0.0	-0.1	-0.1	-0.4	0.0	-0.1	-0.1	0.5	0.3	0.4	-0.2	0.3	-0.1	0.3	0.5	-0.5	0.4	0.0	0.1	0.6	0.5	0.2	-0.1	0.3	0.0	0.1	0.6	0.5	-0.2	-0.2	0.4	0.4	-0.0	1.0