Earnings inequality, the business cycle, and the life cycle

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Abstract

We investigate the relationship between short run macroeconomic conditions and earnings inequality. In our empirical work we establish a set of stylized facts: (1) earnings inequality is counter-cyclical; (2) the bottom quintile of the earnings distribution is the most volatile; (3) business cycles have a low or no impact on wage inequality, but they have a strong impact on hours worked inequality; and (4) the impact of an economic contraction on inequality is weaker in economies with higher levels of education. Then, to explain these observations we develop a stochastic Ben-Porath model of human capital accumulation with life cycle dynamics.

Keywords: Inequality; Business cycles; Human capital accumulation

JEL Codes: I24, E32, E24

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1 Introduction

Several developed countries have experienced a significant increase in wage and earnings inequality starting from the 1970s (see Krueger et al., 2010, for an overview of the empirical facts on inequality). The literature has extensively studied the long run trend in inequality and has identified several causes. These include changes in the demand and supply of labor that, combined with labor market institutions, have favored some workers at the expense of others[1]. Researchers have also investigated the impact of short run macroeconomic conditions on inequality. Parker (1999) provides a review of the initial literature, starting with the seminal work of Mendershausen (1946) and Kuznets and Jenks (1953). Parker's survey of the literature (1946-1998) provides strong evidence that economic contractions have a regressive effect on the income distribution, causing inequality to rise during recessions.

Over the last decade several new studies have emerged on the relationship between inequality and business cycles (e.g., Heathcote et al., 2010; Hoover et al., 2009; Barlevy and Tsiddon, 2006). Perhaps the renewed interest in this topic is motivated by the recent global recession, and the desire to understand the likely distributional implications that it created. Heathcote et al. (2010) documented that over the last 50 years earnings inequality tended to increase during recessions, especially at the bottom of the distribution. This effect could persist for several years after the economy has recovered, as it was the case during the recession of 1980-1981. Similarly, Hoover et al. (2009) found that (family) income inequality is counter-cyclical and the lowest income quantile is the most severely affected by unemployment shocks. Furthermore, for a subset of OECD countries, Maestri and Roventini (2012) found a stronger correlation of the business cycle with inequality in hours worked rather than inequality in hourly wages.

This paper contributes to both the empirical and theoretical literature on inequality. In our empirical work, we use state level data on earnings from the Current Population Survey

[1]Labor market changes are traced back to technological progress, capital-skill complementarity, globalization, immigration and changes in access to education, among others. A survey of these studies is reported in Autor and Katz (1999).

(1967-2013) and confirm that: (1) earnings inequality is counter-cyclical; (2) the bottom quintile of the earnings distribution is the most volatile; (3) business cycles have a low or no impact on wage inequality, but they have a strong impact on hours worked inequality. Further, we show for the first time that the impact of an economic contraction on inequality is weaker in economies with higher levels of education.

Next, we develop a theoretical model to explain these stylized facts. Specifically, we incorporate a Ben-Porath (1967) model of human capital accumulation into an RBC setting with life cycle dynamics. Agents are heterogeneous in age and ability. In this context, ability refers to the speed at which individuals learn new skills. The development of our model is influenced by two well known features in labor economics. First, labor earnings vary over the life cycle; and second, the shape of the age-earnings profile depends on education. The model developed is consistent with these labor market features and we show that it can replicate and explain the empirical observations listed above. In particular, we show that economic downturns increase overall inequality because hours worked drop non-homogeneously across individuals. Instead, the impact on hourly earnings is relatively small. Further, the bottom of the earnings distribution is more severely affected because some individuals significantly reduce hours worked in order to increase leisure and education time or to retire sooner. However, this effect is weaker in economies with higher schooling levels. In this case, the earnings distribution is more stable during a business cycle.

The idea that human capital accumulation could affect inequality during recessions is not new to the literature. Barlevy and Tsiddon (2006) show that the cyclicality of inequality depends on who accumulates human capital during recessions. When long run inequality is increasing, the more able individuals acquire more skills during recessions and inequality grows more rapidly. When long run inequality is decreasing, the less able individuals accumulate more human capital during recessions and inequality decreases more rapidly[2]. Our model is similar to Barlevy and Tsiddon (2006) in that agents differ with respect to the productivity at which they learn. However, in their model agents are infinitely lived,

[2]These results apply if the recession is long enough. See Barlevy and Tsiddon (2006) at page 65.

whereas we model overlapping generations of finite lived agents. With respect to their paper, we show that not everyone in the economy benefits from human capital accumulation during recessions. In fact, we show that only the young use education investment to mitigate the impact of business cycle activity. Further, we find that low ability individuals are more likely to invest in human capital during recessions compared to high ability individuals even if long run inequality is not decreasing[3]. This is more in line with U.S. empirical studies showing that, in the last 40 years, education has been especially counter-cyclical for low-ability individuals (Méndez and Sepúlveda, 2012; Alessandrini et al., 2015) even if long run inequality has increased.

Our paper contributes to the theoretical literature on inequality over the business cycle and its determinants. Inequality in our model is generated by differences in individuals' stock of human capital due to age and ability. We abstract from other sources of inequality, such as unemployment and idiosyncratic shocks, which have been studied by others (e.g., Oh, 2014; Morin, 2013; Krusell and Smith, 1998). Nevertheless, our model is able to match 60% of long run earnings inequality observed in the data (measured by the Gini coefficient) and 80% of its business cycle variation. These results emphasize the importance of heterogeneity in age and learning ability as determinants of inequality in the steady state and during economic cycles. One feature that distinguishes our model from these models is its life cycle dynamics. In the literature mentioned above, agents are assumed to be infinitely lived and there are no overlapping generations. To the best of our knowledge this is the first paper that investigates the impact of aggregate shocks on inequality over the life cycle[4].

The rest of the paper proceeds as follows. Section 2 presents the empirical findings regarding inequality and business cycles. We outline the theoretical model in Section 3

[3]In our model long run inequality is kept constant.

[4]Krusell and Smith (1998) studied income and wealth heterogeneity in a model with aggregate shocks but they do not have a life cycle structure. Instead, they attempted to capture some element of a dynamic OLG structure by incorporating preference heterogeneity in the form of stochastic discount factors. Huggett et al. (2011) studied inequality in a model that has an explicit life cycle structure, but there are no aggregate shocks. Business cycle activity has been studied in life cycle models (e.g. Hansen and İmrohoroğlu, 2009; Gomme et al., 2005; Storesletten et al., 2001), but this literature has not looked at how business cycles affect inequality.

and discuss the theoretical results in Section 4. Finally, Section 5 summarizes the main conclusions.

2 Empirical Evidence

2.1 Some facts about inequality and business cycles

We start by computing some of the most commonly used measures of earnings inequality: the Gini coefficient, and various ratios between percentiles of the earnings distribution (e.g. the P90/P10, which is the ratio between the 90th percentile and the 10th percentile of the distribution).

Following Heathcote et al. (2010), we use data on earnings from March CPS (1967-2013) and exclude records if: (i) the respondent earned positive labor income but reported zero annual hours worked, and (ii) the respondent's hourly wage is less than half of the federal minimum wage for the corresponding year[5]. Earnings are defined as labor income plus 2/3 of business income[6]. To be consistent with our theoretical analysis, the sample is restricted to individuals aged 18-64 years. However, the results are robust to the inclusion of individuals older than 64. Using this restricted sample, we use survey weights to compute our inequality statistics.

Figure 1 plots the cyclical components of annual real GDP and the Gini coefficient for earnings in the U.S. over the period 1967 to 2013. Both series have been transformed by taking natural logarithms and de-trended using an HP filter. Between 1967 and 1977, the series were positively correlated. But starting from 1977, inequality moved counter-cyclically. The co-movement between aggregate output and inequality is also confirmed by Table 1. The first two columns report the correlation coefficients between de-trended GDP and de-trended Gini for earnings during two time periods: 1967-2013 and 1977-2013. We report the correlation

[5] This restriction is applied only if the respondent has earned a positive labor income during the year.

[6] Business income includes both farm and non-farm income. Also note that there is a time inconsistency between the interview year and the reference year regarding income variables. Following Heathcote et al. (2010), we do not correct for this inconsistency. Therefore, we assume that in the interview year respondents earn the same income as in the reference year.

for three population groups: all individuals, males and employed males. The table confirms that there is a negative relationship between inequality and GDP during business cycles, especially starting from 1977. In part, this relationship can be explained by the fact that recessions dis-proportionally increase unemployment of young and low-skilled workers, who tend to be at the bottom of the earnings distribution. However, the cyclicality of inequality is also affected by changes in employment at the intensive margin. In fact, the results are robust when we exclude unemployed workers, as shown in the third row of Table 1. It is worth mentioning that these results are not driven by the Great Recession, that is, similar results were obtained for the sample periods 1967-2006 and 1977-2006 (see Table A1 in the Appendix that accompanies this paper).

One may wonder if the cyclicality of inequality is due to changes in hours worked or hourly earnings. For this reason, we calculate the correlation coefficient between (de-trended) GDP and inequality in hours worked and wages. As shown in columns 3-6, hours worked are primarily responsible for the behavior of earnings inequality during recessions. Depending on the time period considered, recessions have a low or no impact on wage inequality. Therefore, earnings inequality rises during a contraction mainly because individuals at the bottom of the distribution work fewer hours, rather than because they earn lower real wages. This still holds when we restrict the sample to employed workers only.

Table 1 also reports the correlation coefficients for some percentile ratios. The ratio P90/P10 is an alternative measure to the Gini coefficient. Instead, the ratios P90/P50 and P50/P10 measure inequality at the top and at the bottom of the distribution, respectively. Overall inequality at the bottom of the distribution moves counter-cyclically, whereas inequality at the top of the distribution moves pro-cyclically. This is consistent with previous studies documenting that the bottom of the distribution is more severely affected by recessions (e.g., Heathcote et al., 2010; Hoover et al., 2009).

2.2 Conditional correlations

We further investigate the relationship between business cycle activity and inequality by estimating the following panel model:

$$ineq_{st} = \alpha_s + t + \beta Z_{st} + \gamma X_{st} + \epsilon_{st} \tag{1}$$

where s and t refer to the state and time period, respectively; α_s denotes state dummies; and t refers to a linear time trend. The dependent variable, *ineq*, refers to a measure of inequality. Next, Z is a proxy for macroeconomic conditions, and for our main specification we will use state-level GDP since there is significant variation in economic conditions among states. Finally, X is a vector including state-level control variables: mean years of schooling, labor force participation rate and total population.

State-specific GDP is obtained from the Bureau of Economic Analysis, while the other variables are estimated from CPS. Summary statistics are reported in Table 2. Note that CPS has two main advantages. First, it provides reliable estimates at the state level. Second, its sample size and time coverage allow to estimate a time series for inequality at the state level that is sufficiently long. In particular, we have information on 51 states (50 states plus the District of Columbia) and 37 years (1977-2013). Complete information on all states is only available starting from 1977. Alternatively one could use data from the Panel Study of Income Dynamics (PSID). However, the small sample size of PSID would not allow to obtain reliable estimates of state-level inequality for different age groups.

Finally, to address the concern that earnings inequality could affect some of the independent variables (e.g. GDP, mean years of schooling), all explanatory variables are lagged by one period.

Table 3 reports the results from the estimation of equation 1 using the Gini coefficient for earnings as the measure of inequality. Standard errors are clustered at the state level and reported in brackets. The main specification is reported in column 3. Since we are interested in short run fluctuations, this specification includes state-specific linear time trends. This is also done to stationarize the GDP series, which is trend-stationary[7]. We also include the interaction between GDP and mean years of schooling (see columns 4-6 of Table 3). This interaction term is introduced to test whether education affects the relationship between GDP and inequality. When the interaction is included, we report the marginal effect of GDP for different values of mean years of schooling. As expected, there exists a negative association between de-trended GDP and earnings inequality, but notice also that the strength of this association is weaker in states with higher levels of education.

Further, we estimate equation 1 using the percentile ratios as dependent variables to confirm whether inequality at the bottom and at the top of the distribution behave differently. The results are reported in Tables 4 and 5. The second table distinguishes between inequality among individuals with at least some post-secondary education (GiniH) and inequality among individuals with a high school diploma or a lower educational attainment (GiniL). Both tables are consistent with the correlation coefficients discussed above and show that inequality at the bottom of the earnings distribution is more severely affected by recessions. It is important to note that this holds for both employed and unemployed workers.

From Tables 3, 4, 5 and the correlation coefficients examined earlier we make four main observations:

Observation 1: There exists a negative association between de-trended GDP and earnings inequality, suggesting that an economic contraction tends to be associated with higher levels of inequality.

Observation 2: Recessions increase earnings inequality especially at the bottom of the distribution.

Observation 3: The association between economic activity and earnings inequality is mainly due to changes in hours worked inequality. On the contrary, wage inequality is more stable

[7]The results of a panel unit-root test (Levin et al., 2002) confirm that, during the time period considered, GDP at the state level is stationary around the trend. As part of a detailed sensitivity analysis, we restricted all states to share a common time trend. Our results were not affected by this restriction. The sensitivity analysis is reported in an Appendix that accompanies this paper.

during business cycles.

Observation 4: The strength of the association between de-trended GDP and earnings inequality depends on mean years of schooling. In particular, an economic contraction is estimated to have a weaker association with earnings inequality in states with higher levels of education.

Before proceeding to our theoretical analysis, it is worth mentioning that a sensitivity analysis was conducted to test the robustness of these results. The sensitivity analysis is discussed in detail in an Appendix that accompanies the paper; but to summarize this analysis, the results are shown to be robust to:

(i) The statistic applied to measure inequality. We have replaced the gini coefficient with percentile ratios and the results hold (see Table 4).

(ii) The variable(s) used to proxy for business cycle activity. We have experimented by using a common measure of economic activity for all states, that is, we used national GDP rather than GDP by state. In addition, we included other measures of economic activity, such as the state level unemployment rate.

(iii) Various other assumptions regarding the specification of equation 1. For example, we experimented by using a common time trend for all states. We also estimated equation 1 using weighted least squares. In this case, States were weighted by their population size. Thus, we give less weight to smaller states, which may suffer from a larger measurement error. Finally, we estimated equation 1 assuming that error terms are heteroskedastic within panels or correlated across states. The results are stable.

3 Model

Our empirical analysis has revealed a set of four stylized facts that relate business cycle activity to measures of inequality. We now attempt to explain these observations by embedding a Ben-Porath life cycle model of human capital accumulation into an RBC setting.

3.1 The economic environment

Our model specification follows Hansen and İmrohoroğlu (2009) and, in particular, Alessandrini et al. (2015). The economy is populated by heterogeneous agents with finite lifetimes who maximize their expected discounted lifetime utility:

$$E_t \sum_{s=1}^{S_{max}} (\prod_{j=0}^{s-1} \varphi_j) \beta^{s-1} U(c_{t,s}, m_{t,s}), \tag{2}$$

where s denotes age, t denotes the time period, E is the expectation operator, β is the discount factor, c is consumption, m is leisure, and φ_j denotes the probability of surviving from period j to period $j+1$. Agents face an uncertain life span and can live at most until age S_{max}. The per-period utility function of households is:

$$U(c_{s,t}, m_{s,t}) = \frac{(c_{t+s-1,s} m_{t+s-1,s}^{\gamma})^{1-\eta}}{1-\eta}, \tag{3}$$

where γ denotes the disutility from non-leisure activities and η is the relative risk aversion parameter.

Given the focus of this study on inequality in labor earnings, age one in the model is set to match the start of one's working (or post high school) life, and this corresponds to age 18 in reality. Each cohort s is populated by θ_s individuals, where $\theta_s = \varphi_{s-1}\theta_{s-1}$ $(s = 2, .., S_{max})$ and $\theta_1 = 1 - \sum_{s=2}^{S_{max}} \theta_s$ so that the sum of cohort shares equals one. Cohort shares are assumed to be constant over time. Within each cohort, agents are heterogeneous because of different levels of ability, i, which is exogenous and constant throughout the life cycle. We consider two ability levels: $i = \{high, low\}$. High ability individuals can accumulate human capital faster than low ability individuals. The fraction of high types within each cohort is denoted by ξ. Further, all individuals are born with no physical capital but they start their life with a positive endowment of human capital. This is to reflect the human capital stock accumulated by students before age 18. During their life, agents can increase their human capital stock by spending time in education. Human capital accumulation, in turn, increases labor productivity and labor income. For model tractability, we abstract from learning-by-doing or on-the-job training. Thus, education is the only type of human capital investment present in the model.

We set mandatory retirement at age S_r. Before retirement, agents optimally allocate their time endowment among three activities: leisure, work, and education. In the retirement period, instead, all available time is allocated to leisure. Since agents do not earn labor income in this period, there is no incentive to study and accumulate human capital. On the contrary, agents can invest in physical capital in both working and retirement periods. For computational reasons, we abstract from unemployment. Therefore, our theoretical results will only regard employed workers rather than the whole labor force. Although unemployment has some effects on inequality, inequality among employed workers represents roughly 77% of inequality among employed, unemployed and individuals out of the labor force, combined. Further, Table 1 documents that the relationship between business cycles and inequality among employed males has become more important over time. This is mainly due to the fact that employment at the intensive margin is sensitive to economic fluctuations. For these reasons, although we abstract from important determinants of inequality, we believe that the model's predictions can provide important insights on the relationship between business cycles and earnings dispersion.

The consumer's problem can be represented in a recursive manner. Let $V(h_{s,i}, k_{s,i})$ be the maximized value of the objective function of an ability-i and age-s agent. $V(h_{s,i}, k_{s,i})$ is the solution of the following dynamic programming problem:

$$V(k_{s,i}, h_{s,i}) = \max_{c_{s,i}, n_{s,i}, e_{s,i}, h_{s+1,i}, k_{s+1,i}} U(c_{s,i}, m_{s,i}) + \beta\varphi_s EV(k_{s+1,i}, h_{s+1,i}) \tag{4}$$

subject to:

$$k_{t+1,s+1,i} = (1 + r_t - \delta)k_{t,s,i} + w_t n_{t,s,i} h_{t,s,i} - c_{t,s,i} + tr_t \quad \textit{budget constraint} \tag{5}$$

$$h_{t+1,s+1,i} = (1 - \delta_h)h_{t,s,i} + \Omega_{s,i} h_{t,s,i} e_{t,s,i}^{\phi_i} \quad \textit{human capital accumulation} \tag{6}$$

$$m_{t,s,i} + n_{t,s,i} + e_{t,s,i} = 1 \quad \textit{time endowment constraint} \tag{7}$$

$$m_{t,s,i}, n_{t,s,i}, e_{t,s,i}, c_{t,s,i}, h_{t,s,i} \geq 0 \quad \textit{non-negativity constraints} \tag{8}$$

$$n_{t,s,i} = 0 \ for \ s = S_r : S_{max} \quad \textit{retirement constraint} \tag{9}$$

where k is physical capital, h is human capital, e is time spent studying, n is hours worked, r is the rental rate of physical capital, w is the wage rate, δ is the physical capital depreciation rate, δ_h is the human capital depreciation rate, ϕ determines how fast agents can accumulate human capital through education and tr denotes government transfers from deceased agents to surviving agents. The parameter Ω represents the productivity in learning, which depends on age s and ability i. We will revisit these parameters when the model is calibrated in Section 3.3.

In case an individual experiences early death, the government redistributes her/his assets, k, equally among surviving agents in the economy. Given the focus of the paper, the role of the government is limited to the redistribution of assets from deceased to surviving agents.

Finally, competitive firms produce output Y by using efficiency units of labor L, and physical capital K. The production technology is given by a Cobb-Douglas function:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{10}$$

where α is the physical capital share of output and z_t is the aggregate technology level, which follows an AR(1) process: $ln(z_t) = \rho ln(z_{t-1}) + \varepsilon_t$ with $\varepsilon_t \sim N(0, \sigma^2)$. In equilibrium, the prices of the production factors equal their marginal products:

$$w_t = (1 - \alpha) z_t K_t^{\alpha} L_t^{-\alpha}, \tag{11}$$

$$r_t = \alpha z_t K_t^{\alpha-1} L_t^{1-\alpha}. \tag{12}$$

3.2 Stationary equilibrium

Given the initial physical and human capital stocks distributions, and the productivity sequence $\Omega_{s,i}$, the equilibrium is a collection of policy rules for each ability type i, $c_{s,i}(k_{s,t,i}, h_{s,t,i}, K_t, L_t, z_t)$, $n_{s,i}(k_{s,t,i}, h_{s,t,i}, K_t, L_t, z_t)$, $e_{s,i}(k_{s,t,i}, h_{s,t,i}, K_t, L_t, z_t)$, $h_{s+1,i}(k_{s,t,i}, h_{s,t,i}, K_t, L_t, z_t)$ and $k_{s+1,i}(k_{s,t,i}, h_{s,t,i}, K_t, L_t, z_t)$, and the prices of production factors $\{w_t, r_t\}$ such that[8]:

1. The individual policy rules solve each consumer's maximization problem.
2. Factor prices $\{w_t, r_t\}$ equal their marginal products.
3. The market-clearing condition is satisfied:

$$z_t K_t^{\alpha} L_t^{1-\alpha} = C_t + K_{t+1} - (1-\delta)K_t. \tag{13}$$

4. The government budget constraint is satisfied:

$$tr_t = \sum_{s=1}^{S_{max}} \left(k_{s,t,high}\xi + k_{s,t,low}(1-\xi)\right)(1-\varphi_s)\theta_s, \tag{14}$$

5. Individual decisions are consistent with aggregate outcomes:

$$L_t = \sum_{s=1}^{S_r-1} \left(n_{s,t,high}h_{s,t,high}\xi + n_{s,t,low}h_{s,t,low}(1-\xi)\right)\theta_s, \tag{15}$$

$$K_t = \sum_{s=1}^{S_{max}} \left(k_{s,t,high}\xi + k_{s,t,low}(1-\xi)\right)\theta_s. \tag{16}$$

[8] The algorithm we use to solve for the model's equilibrium is described in detail in Heer and Maussner (2009).

3.3 Calibration

The calibration is targeted to US data. Consistent with previous papers in the literature[9], one model period corresponds to one year. Since we abstract from several factors affecting education and labor market decisions by females (e.g. fertility, home production, social norms, gender pay gap), we calibrate the model using data on males only. Table 6 reports the calibrated values as well as the targets of the calibration. Specifically, the maximum number of periods, S_{max}, is set to match the life expectancy at age 18 of males born in 1960 estimated by Bell and Miller (2002), while S_r is set to match the ratio of retired people to active population estimated from 1990 Population Census[10]. Survival probabilities are taken from the life tables estimated by Bell and Miller (2002)[11].

The depreciation rate of physical capital, δ, and the discount factor, β, are set to 6% and 0.969, respectively, in order to match the average annual real interest rate and the average physical capital to output ratio. These values also imply a capital share of output of 0.36. The disutility of non-leisure activities, γ, is set to produce an average time spent working of 0.33. The Solow residual parameters are set to ρ =0.814 and σ =0.0142. These values are the annual equivalents to the parameters estimated by Prescott (1986) for quarterly frequencies[12]. Finally, the risk aversion parameter, η, is set to match output volatility observed in U.S. data. The literature uses values between 1 and 3, and our calibrated parameter falls within this range.

For the fraction of high types, ξ, we considered values in the range $\xi = 0.59$ to $\xi = 0.42$. The higher value represents the average fraction of high-school graduates enrolling in college during the period 1967-2013 (source: Bureau of Labor Statistics). The lower value is obtained using data on cognitive tests scores from the National Longitudinal Survey of Youth

[9] For example, Hansen and İmrohoroğlu (2009), İmrohoroğlu et al. (1995) and Gomme et al. (2005).

[10] Having endogenous retirement would not significantly change the model's predictions. Further, mandatory retirement is necessary for the model to match the fraction of retired individuals to active population observed in the data.

[11] We use the survival probabilities estimated for males born in 1960. Although survival probabilities differ by cohort due to changes in life expectancy over time, differences between the 1960 cohort and subsequent cohorts are minimal.

[12] See Heer and Maussner (2009), page 549.

1979. Specifically, 0.42 is the fraction of individuals with an Armed Forces Qualification Test (AFQT) score above the mean score in 1980, when the test was administered. However, we found that the inequality statistics in the model were not particularly sensitive to the values within this range, and therefore we selected the midpoint. Setting $\xi = 0.50$ implies that the population of the model is evenly divided between high and low types.

The depreciation rate of human capital is set to 0.005. This value is consistent with several papers in the literature that use a depreciation rate of human capital close to zero. For example, $\delta_h = 0$ in Heckman et al. (1998), $\delta_h = 0.005$ in DeJong and Ingram (2001) and $\delta_h = 0.018$ in Manuelli and Seshadri (2009).

The parameter ϕ_i is set to match the average time spent in education by high and low ability males over their life cycle. Data on time spent studying are from the American Time Use Survey (ATUS, 2003-2013)[13]. Empirically, we use educational achievement as proxy for ability. A survey respondent is considered to be a high type if he has a post-secondary degree or is currently enrolled in university/college. Instead, the group of low types includes respondents with some PSE education but no degree, as well as respondents with a high-school diploma only or lower educational achievements[14]. Given our classification, the time allocated to education by high ability individuals is 5 times larger than that of low types.

The parameter Ω is estimated using equation 6 as follows:

$$\Omega_{s,i} = \frac{h^*_{s+1,i} - (1-\delta_h)h^*_{s,i}}{h^*_{s,i} e^{*\phi_i}_{s,i}}. \tag{17}$$

where $h^*_{s,i}$ is the steady state human capital stock for age s and ability type i, while $e^*_{s,i}$ is the time spent studying in the steady state for an age-s and ability-i agent. The education sequence, $e^*_{s,i}$, is estimated using data on study hours from ATUS. To estimate human capital

[13]Our definition of studying includes the following activities: taking classes (code: 060100) and doing related research/homework (code: 060300). We use survey weights to estimate the average time spent studying.

[14]Individuals that have not completed a PSE degree yet but are currently enrolled are considered high types. Since we cannot observe their future achievements yet, we assume that they will complete their program. On the contrary, PSE drop outs are considered low types. These individuals are not currently enrolled in school but completed some post-secondary education in the past without obtaining a degree.

stocks, $h^*_{s,i}$, we use data from the Panel Study of Income Dynamics (PSID, 1968-2013)[15] on labor earnings and hours worked for males only. We calculate the sequence $h^*_{s,i}$ by following Hansen (1993). Specifically, we first obtain mean hourly earnings for each ability and age group and then calculate the efficiency weights using $h^*_{s,i} = HE_{s,i}/HE$, where $HE_{s,i}$ is mean hourly earnings for age-s and ability-i individuals, while HE is mean hourly earnings for the whole population[16]. As previously discussed, respondents with a post-secondary degree or enrolled in PSE in 2013, which is the last available year, are considered high types. Respondents with no post-secondary degree are considered low types. Note that, although the majority of individuals complete post-secondary education early in the life cycle, some do not. Using panel data from the PSID is particularly useful in this case because it allows us to follow individuals over time and take into account that some individuals may complete post-secondary education later in their life cycle.

The calibration procedure for ϕ_i and Ω_i can be summarized as follows. For both types $i = \{high, low\}$, we make an initial guess for ϕ_i so that we can generate the productivity series Ω_i. We then solve for the equilibrium policy rules and prices and run a simulation to obtain steady state profiles for education (e^*_{si}). If the average time devoted to education over the life cycle by each type does not match the evidence from the data, we update our guesses for ϕ_i and continue this process until convergence. It is worth mentioning that both parameters ϕ_i and $\Omega_{s,i}$ depend on ability. However, the model's predictions are mainly affected by Ω. Whether we distinguish between ϕ_{low} and ϕ_{high} or we use a common value does not alter the main predictions. However, separate ϕ values allow us to match exactly the average time spent studying for the two groups.

Figure 2 shows the estimated human capital and education profiles, $h^*_{s,i}$ and $e^*_{s,i}$, for each ability type as well as the corresponding profiles predicted by the model. The figure also shows a similar comparison for the life cycle profile of efficiency wage, $h_{s,i} \times w$. As expected,

[15] Data on earnings and hours are collected during the interview year (e.g. 1968) but refer to the previous year (e.g. 1967).

[16] For each ability type, we estimate h^* and e^* for 5 age groups (18-24, 25-34, 35-44, 45-54, 55-64) and then interpolate the values to obtain the whole sequence.

young individuals allocate more time to education, and therefore accumulate human capital faster than older individuals. This is especially true for young high types. As a result, their wages increase relatively fast early on. The calibrated model is able to reproduce the profiles obtained from US data fairly well. However, there is a discrepancy between the model and the data regarding the human capital profile late in the life cycle, especially for high types. This may be due to the fact that, although individuals do not allocate a significant amount of time to education towards the end of their life, in reality they may still invest in human capital through learning-by-doing or on-the-job training. Our model abstracts from these forms of human capital accumulation and, therefore, predicts a decrease in human capital due to depreciation and the absence of investments in education.

4 Theoretical Results

For our theoretical analysis, we focus on the same measures of inequality that we used in our empirical analysis: the Gini coefficient of earnings, P90/P50, P90/P10 and P50/P10. We also analyze the percentage of earnings held by each quantile of the earnings distribution.

4.1 The steady state and inequality

Although the primary objective of this paper is to study how earnings inequality is affected by business cycle activity, before this can be accomplished it is necessary to analyze how inequality is created in the model's steady state.

Figure 3 shows the steady state life cycle profiles for several variables of interest. Since high types are more productive in learning than low types of the same age, they allocate more time to education in the steady state and do not participate in the labor market until age 3 (age 20 in reality). They initially forgo some labor income in order to accumulate human capital, but earn a high labor income later on. Instead, low types start working since the beginning of their life and, therefore, invest less in human capital. With respect to earnings, high types are able to overtake low types around age 8 (age 25 in reality). Low types' earnings are more stable over the life cycle, thus earnings inequality is higher among high types than low types. As already discussed, Figure 2 confirms that these predictions are consistent with U.S. data.

Table 7 reports several inequality statistics for the model (column 1) and the data (columns 2-4). For consistency with the model, we focus on individual-level variables in the data (e.g. individual earnings instead of household earnings)[17]. For the US economy we report inequality statistics for three samples: (i) labor force, (ii) male labor force, and (iii) employed males. Notice that, in general, excluding unemployed workers from the sample has very little effect on the values of the inequality statistics, and this is because unemployed workers account for only a small fraction of the labor force. Therefore, most of the inequality measured by aggregate statistics reflects differences among employed workers.

Using the Gini coefficient as our measure of earnings inequality, the results in Table 7 reveal that the model can account for approximately 60 percent of the inequality observed in the data. In the steady state, earnings inequality arises for two main reasons. First, wages depend on worker efficiency or human capital, and levels of human capital tend to be higher for older workers, and higher productivity types. Second, hours spent working varies over the life cycle, and is higher for middle age workers compared to younger and older workers. Another important fact from Table 7 is that, both in the model and the data, earnings inequality is higher at the bottom of the earnings distribution compared to the top of the distribution (i.e. the P50/P10 ratio is higher than the P90/P50 ratio). Finally, as already discussed in the literature (for example see Krueger et al., 2010), consumption inequality is lower than earnings or income inequality suggesting that individuals are able to smooth consumption over time. Qualitatively our model's predictions are consistent with this empirical regularity, which is not unique to the United States. However, the numerical results indicate that it is more difficult to smooth consumption over the life cycle in the US economy compared to the model economy.

[17]Data on consumption are collected at the household level and then transformed in per-adult-equivalent units.

One variable that the model has some difficult replicating is the inequality that exists between the highest and lowest income earners, that is, the P90/P10 ratio. We investigate the earnings distribution in the model further in Table 8, which show the percentage of earnings held by each quintile of the labor force. The model does reasonably well predicting the percentage of earnings held by individuals in the middle quintiles but cannot match the high percentage of earnings held by the top quintile. This suggest that human capital differences and life cycle characteristics alone are not enough to account completely for the earnings of the wealthiest fifth of the population.

To better explain the sources of inequality in the steady state, Figure 4 is included and shows the life cycle profiles for mean hours worked, earnings and consumption as well as several inequality measures. Since earnings and consumption have different units in the model and in the data, we normalize the values to one at age 23 (40 in reality). Further, when calculating the empirical life cycle profiles, we separate time or cohort effects from age effects. When estimating inequality over the life cycle, one needs to use information on individuals from different time periods, which may not be comparable for several reasons (e.g. differences in returns to education or ability, trade liberalization, changes in education quality, size of birth cohorts, minimum wage/union regulation, etc.). Our focus is on age effects only, thus we remove time effects (i.e. changes that over time affect inequality within age groups) or cohort effects (i.e. differences among cohorts). Following the literature (e.g. Huggett et al., 2011; Heathcote et al., 2010), we assume that time, age and cohort effects are additively separable and we isolate age effects using the methodology in Deaton and Paxson (1994).

The model is consistent with the data in that it produces an inverted-U shape for the profiles of mean hours worked and earnings, while consumption is increasing in age. According to the model, this depends on the fact that the learning productivity and, therefore, study hours are decreasing in age. As a result, hours worked and earnings are relatively low initially because young individuals tend to allocate their time to education. However, as agents enter the labor market and reduce study hours, earnings increase until approximately age 25 (42 in reality). After age 25, the marginal utility of leisure overtakes its cost thus agents start allocating more time to leisure, which reduces hours worked and earnings.

On the contrary, inequality over the life cycle follows the opposite pattern. Hours worked inequality and earnings inequality are decreasing in age for very young individuals (until approximately age 10), while they are increasing afterwards. As young high types enter the labor market, the earnings differential between young high and young low types shrinks. However, the gap in earnings widens again as soon as high types accumulate enough human capital to overtake the earnings of low types. Instead, consumption inequality tends to be fairly stable over the life cycle, especially after age 5 (22 in reality).

In summary, in this section we study the long run properties of a model with economic agents that are heterogeneous with respect to age and ability. The Gini coefficient for earnings in the model's steady state (without aggregate or idiosyncratic shocks) is roughly 60% of the average level observed in the data over the 1967-2013 period. In addition, the model is able to reproduce the shape of the life cycle profiles of hours worked, earnings, and consumption inequality. These results are consistent with previous studies in the literature that emphasize the importance of heterogeneity in learning ability as a source of earnings inequality (e.g. Huggett et al., 2006, 2011; Barlevy and Tsiddon, 2006). In the next section, we show that aggregate shocks will also have an impact on earnings inequality.

4.2 The business cycle and inequality

In this section, we study how our measures of inequality are affected by business cycle activity. Our analysis begins with a discussion of Table 9, which compares the average business cycle statistics obtained from 500 simulations of the model with the same statistics calculated using U.S. data. The model's ability to mimic key aspects of business cycle behavior is important, otherwise we cannot be confident that the model will do a good job explaining fluctuations in the levels of inequality. Our model is consistent with the data and other specifications of the RBC model in the macroeconomics literature, in that consumption is less volatile than output; investment is much more volatile than output; and consumption, investment and hours worked are all strongly pro-cyclical. It is also the case that, in both the model and the data, hours worked are more volatile for those without a post-secondary education. Further, inequality is counter-cyclical, which implies that it rises during a contraction. Both in the model and in the data, inequality at the bottom of the distribution (P50/P10) is about 3 times more volatile than inequality at the top of the distribution (P90/P50). Perhaps the main shortcoming of the model is that the volatility in hours worked is low compared to the data.

To help explain the model's predictions pertaining to business cycle activity, we plot the impulse response functions for the main variables of interest to a negative technology shock (see Figure 5). Consistent with previous findings in the RBC literature, a negative shock reduces factor prices and this causes a decline in both hours worked and physical capital investment. The decline in wages and hours worked causes earnings and output to drop. Consumption is pro-cyclical as it drops with output. However, education and human capital are counter-cyclical for both types of agents. In fact, the deviation of education with respect to the steady state is higher for low types than high types. This result is due to the fact that low types face a lower opportunity cost of education and a higher marginal benefit of human capital. Previous papers in the literature (e.g. Méndez and Sepúlveda, 2012; Alessandrini et al., 2015) have empirically confirmed this finding.

In the remainder of this section we revisit our empirical analysis and attempt to explain the four stylized facts that link business cycle activity to inequality.

Why does an economic contraction cause earnings inequality to rise? The last three panels of Figure 5 show the change over time of the Gini coefficients for wages, hours worked, and earnings. In the model, overall earnings inequality (measured by the Gini coefficient) is higher during a recession compared to the steady state. This result depends on both types of heterogeneity (age and ability) that are built into the model. To see this consider Figure 6, which reports the percentage change in wages, hours worked and earnings one year after the shock by age and ability type. First, notice that young high types reduce their hours worked significantly after the shock, and therefore they suffer a strong reduction in earnings. Thus, inequality rises between young and old high types. Next, notice that low types (particularly old low types) reduce hours worked more compared to high types of the same age. Thus, the earnings differential between high types and low types increases.

Why does an economic contraction have a regressive effect on the earnings distribution? Figure 7 shows the impulse response functions of the percentages of earnings held by each quantile. Right after the shock, the percentage of earnings held by the first three quantiles drops, while the percentage of earnings held by the 4th and 5th quantiles increases. Further, the bottom quantile is hurt the most. The bottom quintile of the earnings distribution consists of young agents that have not yet acquired much human capital. These are the agents with the lowest wage rates and that benefit the least by working during an economic contraction. As a result, hours worked and earnings are the most volatile for the bottom quintile of the earnings distribution.

Why is the association between business cycle activity and earnings inequality due mainly to changes in hours worked inequality rather than changes in wage inequality? Figure 5 shows that although the wage rate is responsive to technology shocks, wage inequality is not. In the model, wage inequality arises because of differences in human capital levels. An economic contraction reduces the education gap between high and low types, because it encourages low types to study. However, since low types are less productive in learning and accumulate human capital at a low pace, the reduction in education inequality does not translate into an equivalent reduction in human capital inequality. As a result, wage inequality is not strongly affected by the shock.

Why does schooling mitigate the impact of an economic contraction on earnings inequality? In the model, the agents with the highest levels of schooling are the old (ages 27-64) and particularly the old high types. These agents accumulate a lot of human capital during their lives, and therefore they are very reluctant to leave the labor market, even during a contraction. In fact, the employment level for older high types is the most stable of any group, and therefore their earnings levels are the most stable during a business cycle. This suggests that the more educated the economy is, the more stable will be the Gini coefficient for earnings.

5 Conclusions

This paper investigates the impact of macroeconomic conditions on earnings inequality. Studying this topic is particularly important to further understand the determinants of economic inequality as well as to provide guidance on the allocation of governments' resources during business cycles. Our results show that negative technology shocks increase earnings inequality. However, the impact is heterogeneous. Young high-ability individuals and old low-ability individuals are hurt the most. They suffer the biggest reduction in earnings compared to other population groups. This is mainly due to the fact that their hours worked drop significantly compared to other workers. The heterogeneous drop in hours and earnings has important consequences on the earnings distribution. Young high types and old low types earn less than the average worker in normal times, and even less after a negative aggregate shock. Thus, recessions affect the bottom of the distribution more severely. The first quantile of the earnings distribution is hurt the most.

However, education mitigates the rise of inequality during recessions. The more educated the economy is, the more stable the earnings distribution is during recessions. This result is confirmed empirically using data from CPS (1977-2013): the increase in inequality during economic contractions is lower in states with a higher level of education, measured by mean years of schooling.

Tables

Table 1: Contemporaneous correlations between GDP (Y) and inequality

	Corr(Gini earnings,Y)		**Corr(Gini wages,Y)**		**Corr(Gini hours,Y)**	
	1967-2013	1977-2013	1967-2013	1977-2013	1967-2013	1977-2013
All	-0.27	-0.37	-0.08	-0.11	-0.43	-0.50
Males	-0.19	-0.34	-0.10	-0.16	-0.41	-0.46
Employed males	-0.003	-0.15	0.03	-0.10	-0.37	-0.38
	Corr(P90/P50,Y)		**Corr(P90/P10,Y)**		**Corr(P50/P10,Y)**	
	1967-2013	1977-2013	1967-2013	1977-2013	1967-2013	1977-2013
Employed males	0.08	0.21	0.05	-0.09	0.01	-0.22

When calculating Gini coefficients we restrict the sample to individuals aged 18-64. See Figure 1 for a description of the data. Percentile ratios refer to the earnings distribution. We do not report percentile ratios for the whole sample and for males because the income levels of the corresponding 10th percentiles are equal to zero.

Table 2: Summary statistics (51 states, 1977-2013)

Variable	Mean	Std. deviation	Minimum	Maximum
State population (millions)	5.23	5.81	0.41	38.0
Mean years of schooling	12.60	0.62	10.51	14.37
Labor force participation (%)	58.9	5.91	32.9	73.1
Unemployment rate (%)	6.08	2.09	2.30	17.4
State-level GDP (billions $2009)	203.78	264.19	9.53	2,072.15
National GDP (billions $2009)	10,649	3,166	5,937	15,583
Gini	0.54	0.04	0.44	0.71
GiniH	0.48	0.05	0.31	0.64
GiniL	0.54	0.04	0.42	0.74
P90/P10	8.04	1.49	4.20	16.67
P90/P50	2.24	0.26	1.61	3.38
P50/P10	3.59	0.59	2.22	6.67

Table 3: Earnings inequality and macroeconomic conditions

Dependent variable:				$\ln(\text{Gini}_{s,t})$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(GDP_{s,t-1})$	-0.01	-0.13***	-0.12***	-1.04***	-1.05***	-0.66***
	(0.02)	(0.04)	(0.04)	(0.13)	(0.13)	(0.11)
$School_{s,t-1}$			-0.09***	-0.90***	-0.89***	-0.50***
			(0.01)	(0.11)	(0.11)	(0.09)
$ln(GDP_{s,t-1}) \times School_{s,t-1}$				0.07***	0.07***	0.04***
				(0.01)	(0.01)	(0.01)
$Population_{s,t-1}$					3.64*	3.04*
					(1.91)	(1.58)
$Participation\ rate_{s,t-1}$						-0.61***
						(0.06)
Marginal effect of ln(GDP) at School=						
10 years of schooling				-0.30***	-0.32***	-0.22***
11 years of schooling				-0.23***	-0.24***	-0.17***
12 years of schooling				-0.16***	-0.17***	-0.13***
13 years of schooling				-0.08***	-0.10***	-0.09***
14 years of schooling				-0.01	-0.02	-0.04
15 years of schooling				0.06	0.05	-0.002
Linear time trend	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓
State fixed eff.× time trend		✓	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R-squared	0.60	0.69	0.72	0.74	0.75	0.78

Population is in hundreds of millions. Robust standard errors (clustered at the state level) are in parentheses. All regressions include a constant term. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Percentile ratios and macroeconomic conditions

Dependent variable	ln(P90/P50)		ln(P90/P10)		ln(P50/P10)	
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(GDP_{s,t-1})$	-0.03	-0.04	-0.47***	-0.46***	-0.44***	-0.43***
	(0.03)	(0.04)	(0.12)	(0.12)	(0.11)	(0.11)
$School_{s,t-1}$		0.00		0.11**		0.10***
		(0.02)		(0.04)		(0.04)
$Population_{s,t-1}$		0.24		-1.77		-2.01
		(1.54)		(3.96)		(3.58)
$Participation\ rate_{s,t-1}$		0.15		-0.30		-0.45*
		(0.09)		(0.27)		(0.23)
Linear time trend	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓
State fixed eff.× time trend	✓	✓	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R-squared	0.73	0.73	0.37	0.38	0.35	0.35

Population is in hundreds of millions. Robust standard errors (clustered at the state level) are in parentheses. All regressions include a constant term. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Inequality by educational attainment

Dependent variable	ln(GiniH)			ln(GiniL)		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(GDP_{s,t-1})$	-0.05**	-0.05*	0.04	-0.20***	-0.16***	-0.88***
	(0.02)	(0.03)	(0.15)	(0.06)	(0.04)	(0.12)
$School_{s,t-1}$		0.04*	0.11		-0.02**	-0.66***
		(0.02)	(0.13)		(0.01)	(0.10)
$ln(GDP_{s,t-1}) \times School_{s,t-1}$			-0.01			0.06***
			(0.01)			(0.01)
$Population_{s,t-1}$		1.12	1.11		3.35	3.44**
		(1.08)	(1.13)		(2.00)	(1.33)
$Participation\ rate_{s,t-1}$		-0.13	-0.14*		-0.87***	-0.75***
		(0.08)	(0.08)		(0.08)	(0.08)
Linear time trend	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓
State fixed eff. × Time trend	✓	✓	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R-squared	0.72	0.72	0.72	0.64	0.74	0.75

Population is in hundreds of millions. Robust standard errors (clustered at the state level) are in parentheses. All regressions include a constant term. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Calibration of the model

Parameter	Calibrated value	Set to target	Target values US economy	Values from the model
S_{max}	60	life expectancy at age 18	58.99	58.47
S_r	47	ratio of retired people to active population	21.6%	20.7 %
γ	1.84	n^*	0.33	0.33
η	1.05	σ_Y	1.38	1.38
δ	0.06	average annual real interest rate	6%	6%
β	0.966	average physical capital to output ratio	3	3.06
ϕ_{high}	0.122	e^*_{high}	0.026	0.026
ϕ_{low}	0.05	e^*_{low}	0.005	0.005

Following Hansen and İmrohoroğlu (2009), the target values for n^* and K^*/Y^* are 0.33 and 3, respectively.

Table 7: Inequality in the steady state - individuals aged 18-64

Measure	Variable	MODEL	DATA *labor force*	DATA *male labor force*	DATA *employed males*
Gini:	*Earnings*	0.26	0.44	0.42	0.41
	Wage	0.15	0.48	0.46	0.40
	Hours worked	0.16	0.18	0.17	0.15
	Income	0.69	0.43	0.41	0.40
	Consumption	0.14	0.32	0.31	0.31
	Education	0.82	0.97	0.97	0.99
P90/P10:	*Earnings*	4.40	11.62	8.71	7.74
P90/P50:	*Earnings*	1.71	2.43	2.24	2.22
P50/P10:	*Earnings*	2.58	4.78	3.89	3.50

Data on earnings, wages, hours worked and income are from March CPS 1967-2013. Data on consumption are from the Consumer Expenditure Survey (CEX, 1980-2007). We focus on durable goods and we use the dataset provided by Heathcote et al. (2010). Data on education are from ATUS 2003-2013. A respondent is considered employed if he worked at least 5 hours during the week before the interview. We include zero and negative values when calculating the Gini coefficient and the percentile ratios.

Table 8: Earnings distribution in the model and the data

	Percentage of earnings held by				
	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile
Model	7.79	14.59	19.52	24.89	33.21
Data (labor force)	3.25	9.82	15.89	23.59	47.44
Data (male labor force)	4.03	10.94	16.46	23.03	45.50
Data (employed males)	4.57	10.94	16.46	23.03	45.00

The data are from March CPS (1967-2013) and refer to individuals in the labor force aged 18-64. The model's statistics refer to individuals aged 1-47.

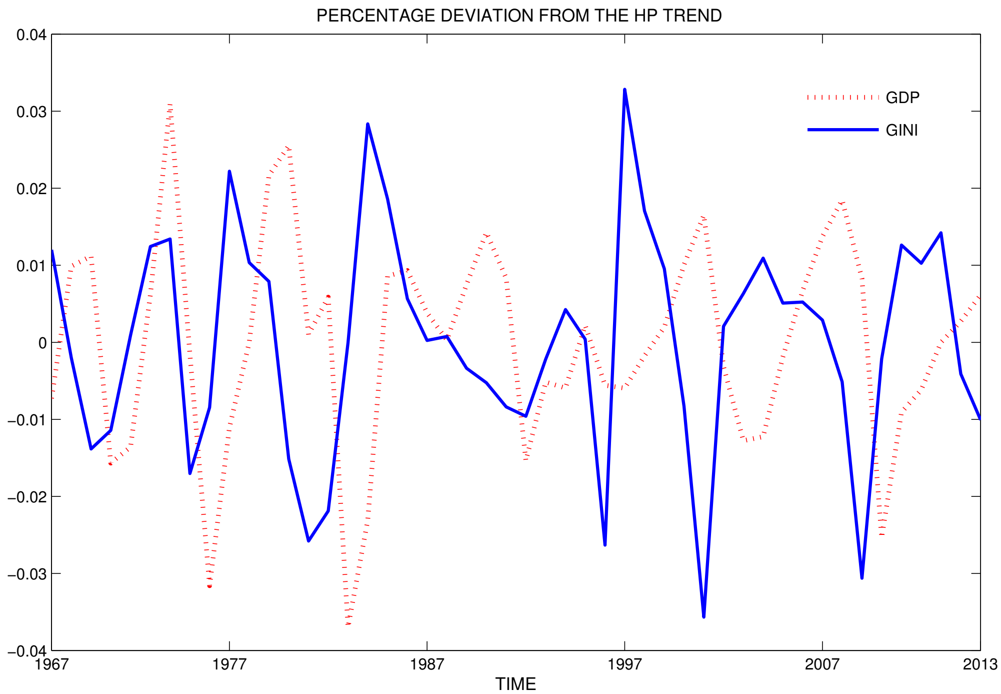
Table 9: Business cycle statistics

X	σ_X		$corr(X_t, Y_t)$	
	DATA	MODEL	DATA	MODEL
Y	1.38	1.38	1	1
C	1.13	0.26	0.91	0.94
I	6.27	6.36	0.93	0.99
N	1.33	0.77	0.84	0.99
N_{high}	0.73	0.51	0.50	0.98
N_{low}	1.70	1.06	0.83	0.99
Gini Earnings	1.14	0.90	-0.13	-0.99
P90/P10	4.84	2.05	-0.12	-0.96
P90/P50	1.46	0.60	-0.05	-0.81
P50/P10	4.31	1.63	-0.12	-0.91

The statistics on inequality are calculated from March CPS (1967-2013) and refer to all individuals in the labor force aged 18-64. Data on output (Y), consumption (C), and investment (I) are obtained from the Bureau of Economic Analysis. Data on aggregate hours worked (N) are obtained using the question 'How many hours did you actually work last week?' from the March CPS (1967-2013). N_{low} and N_{high} denote labor supply of low and high types, respectively. Both actual and simulated series have been transformed by taking natural logarithms and de-trended using an HP filter. We follow Ravn and Uhlig (2002) and set the smoothing parameter to 6.25.

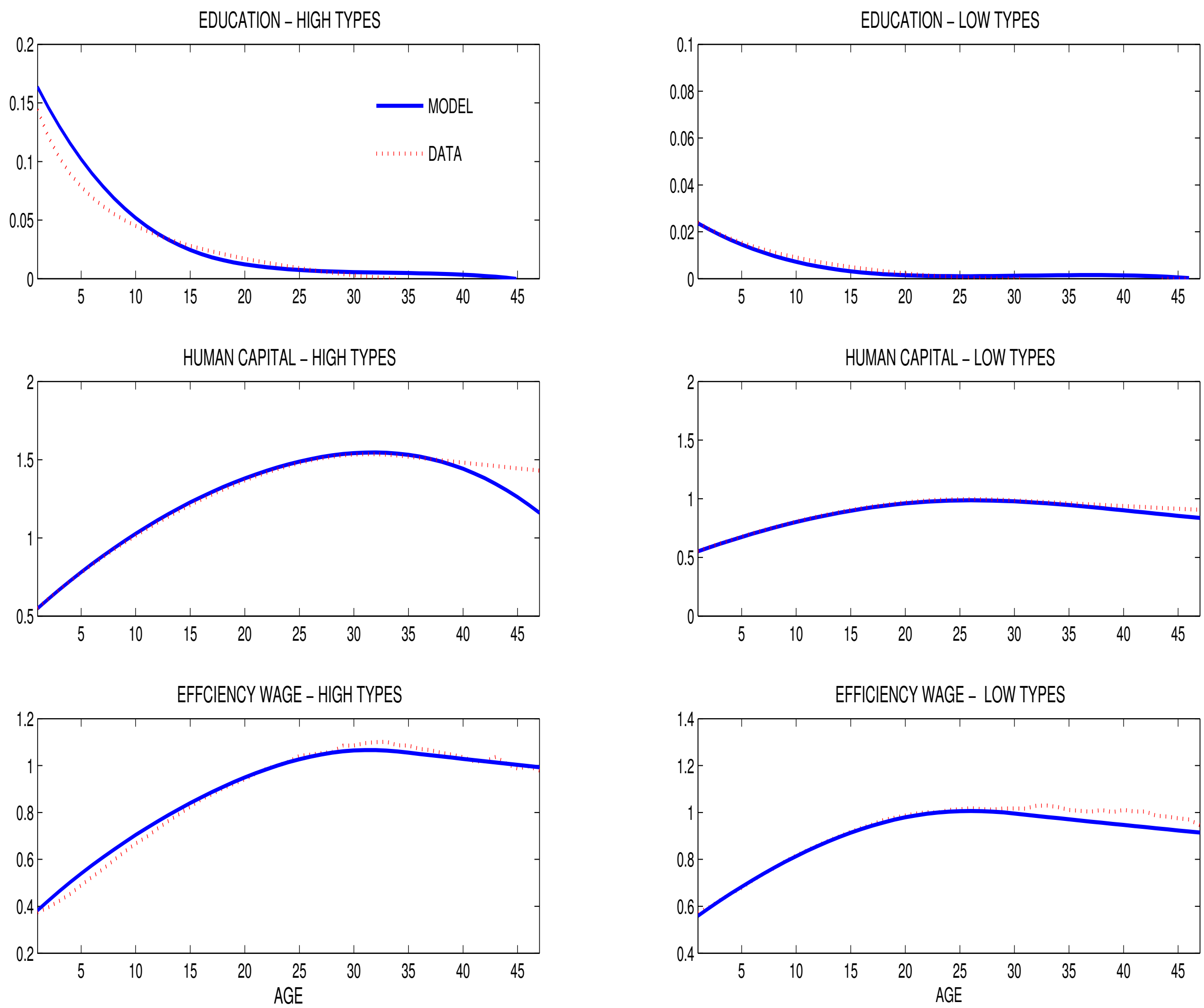
Figures

Figure 1: Earnings inequality and GDP



Earnings inequality is calculated using earnings data from the March CPS (1967-2013). (Real) GDP is from the Bureau of Economic analysis (chained 2009 dollars). Since the Gini coefficient is calculated from CPS on an annual basis, we use annual GDP. All series have been logged and detrended using the Hodrick-Prescott filter. Following Ravn and Uhlig (2002), we set the HP smoothing parameter to 6.25.

Figure 2: Life cycle profiles by ability type: model versus data



Note: since efficiency wages have different units in the model and in the data, we normalize wages to one at age 23 (40 in reality).

Figure 3: Life cycle steady state profiles

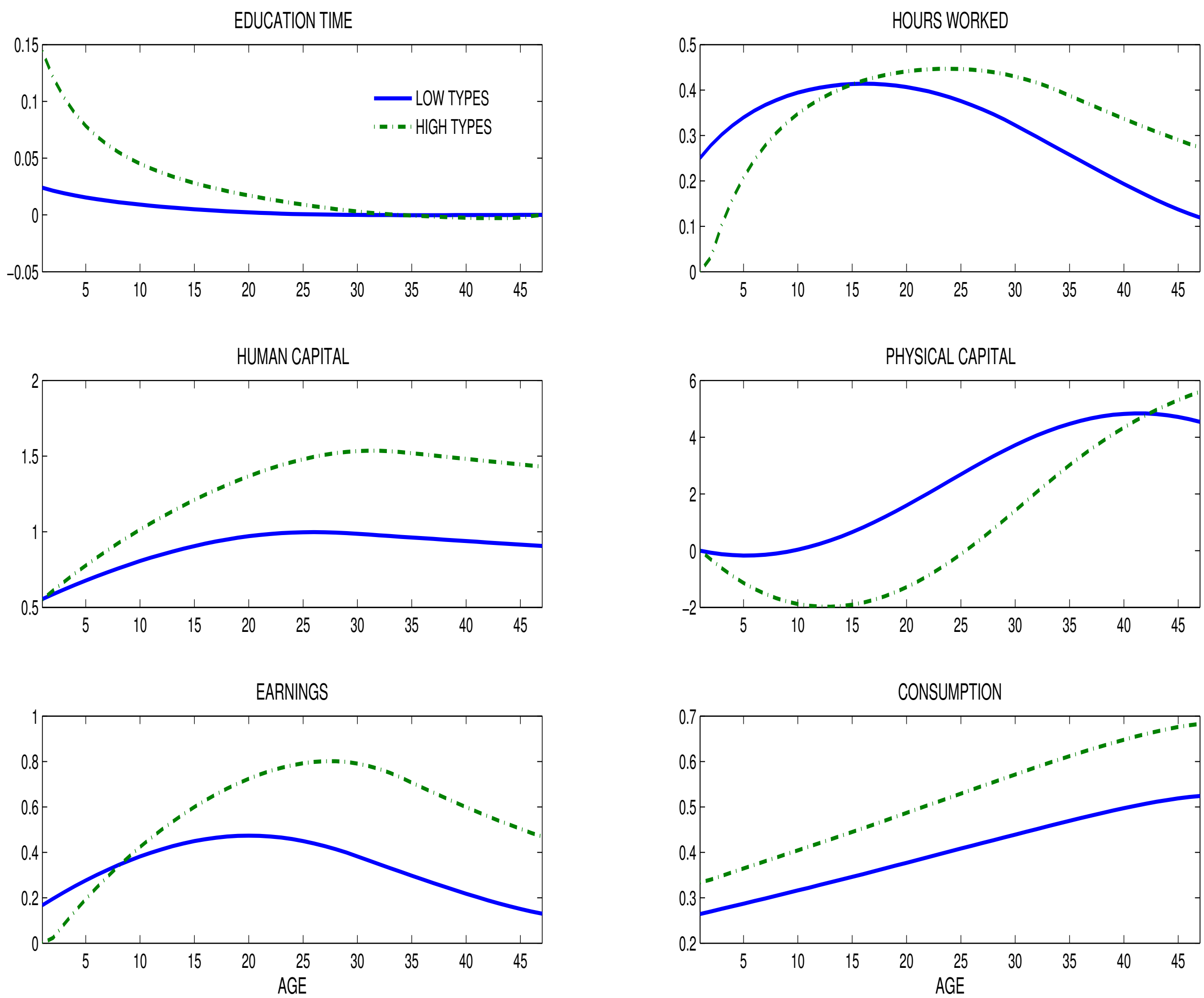
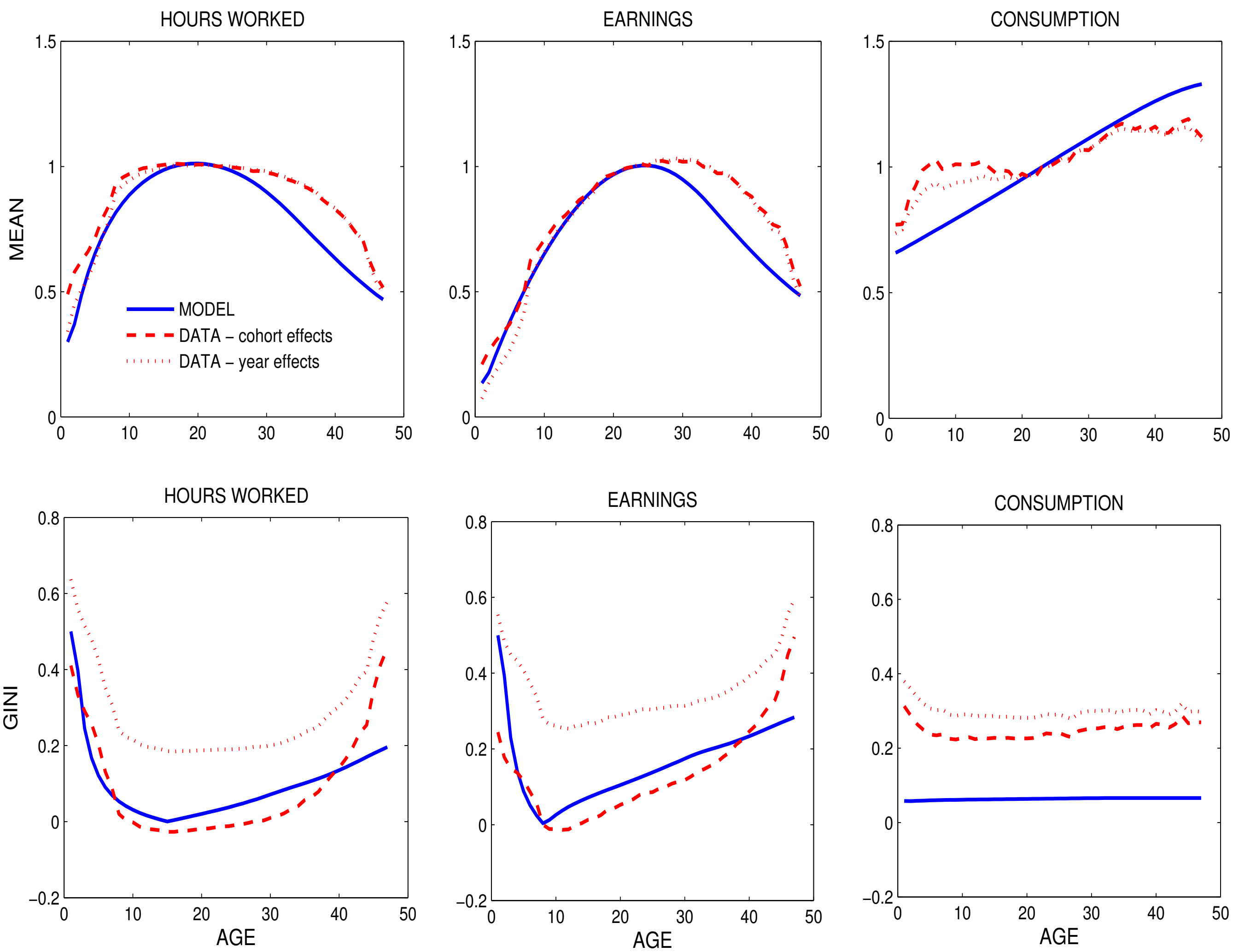
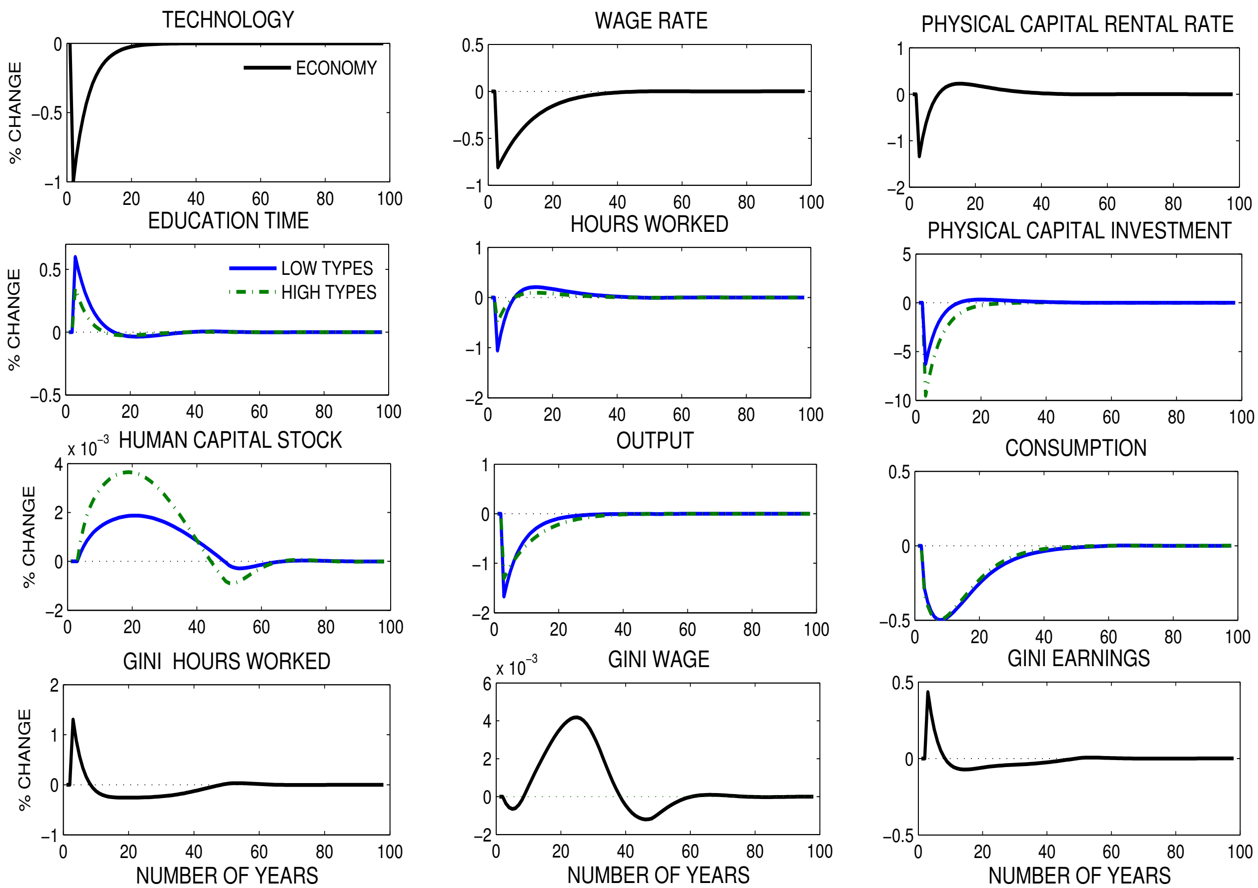


Figure 4: Life cycle profiles: model versus data



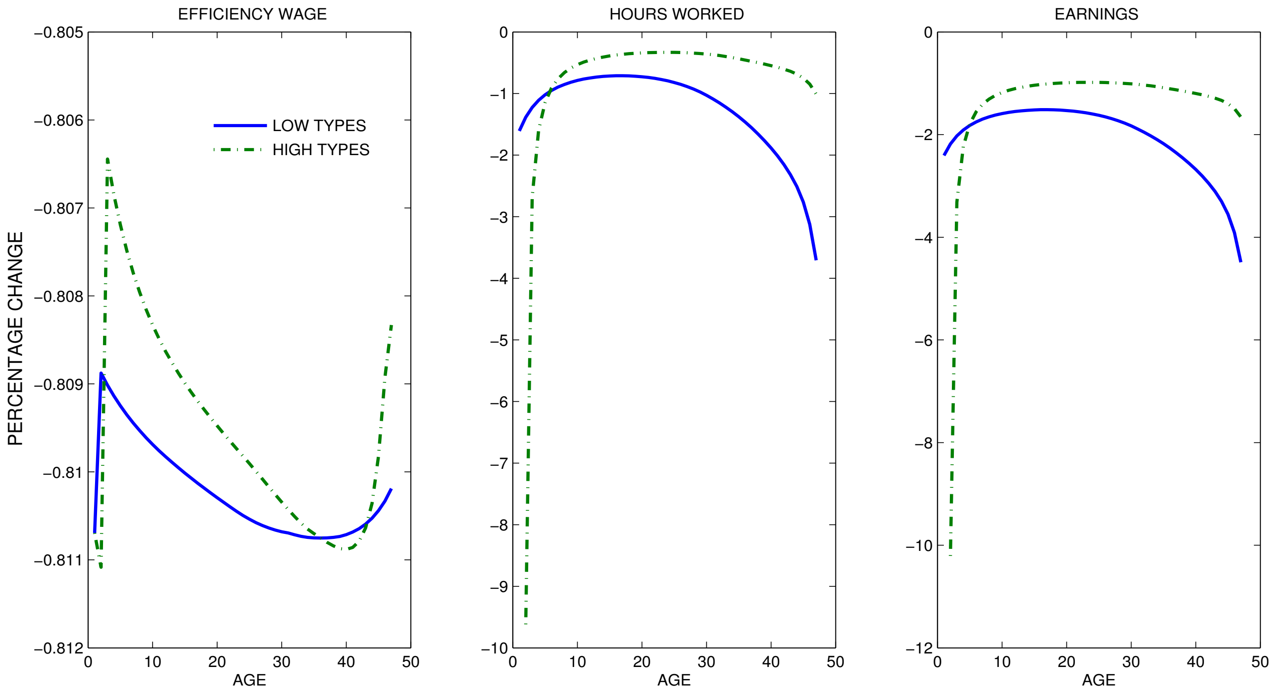
Notes: When removing time effects, 1967 is the reference year. When removing cohort effects, 1967 is the reference cohort.

Figure 5: Impulse response functions



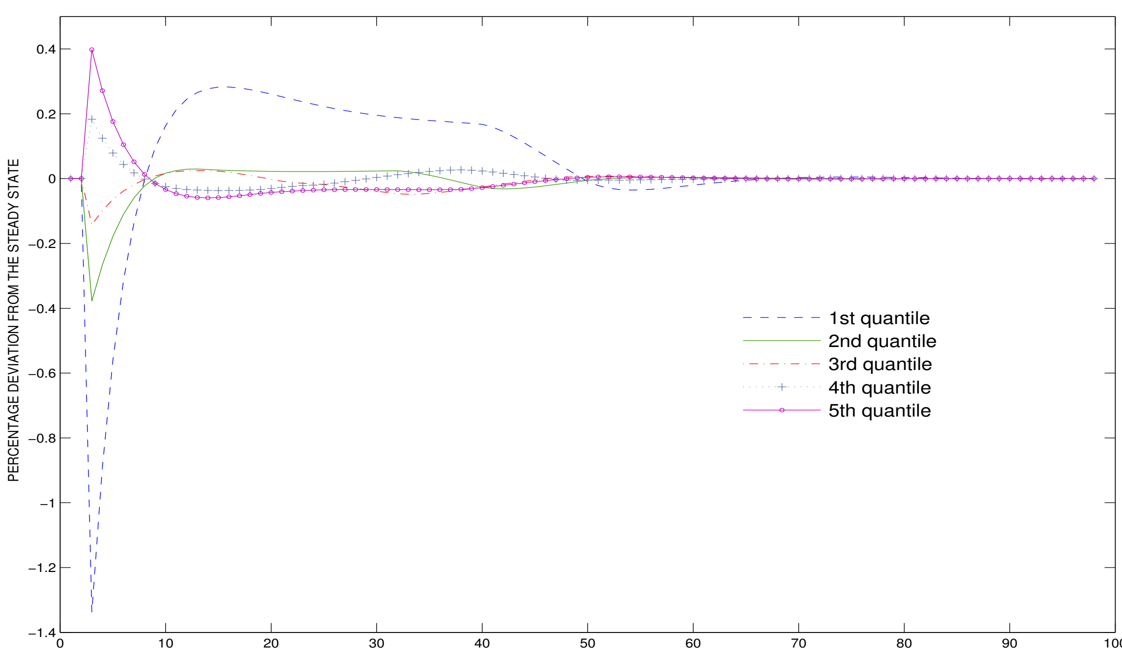
The horizontal axis reports the number of years after the negative shock, while the vertical axis reports the percentage change from the steady state for each variable.

Figure 6: Percentage change in wage, hours worked and earnings one year after the shock



The horizontal axis refers to age, while the vertical axis reports the percentage change from the steady state for each variable.

Figure 7: The impact of a negative shock on the earnings distribution



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Appendix: Sensitivity Analysis

In this section, we test the robustness of our empirical findings.

First, we have re-calculated the correlation coefficients presented in Section 2 excluding recent years (2007-2013) to test if the results are partially driven by the recent recession. The results are robust (see Table A1).

Second, our empirical results are not unique to the Gini coefficient. For example, the same features of the data can be observed from the estimation of equation 1 using percentile ratios (see, for example, Table 4 in the main text).

Third, in our main specification we used real GDP by state as a proxy for macroeconomic conditions. This is a natural choice but it has some shortcomings. Real GDP by state is only available starting from 1977 and it is not consistently estimated over time due to a change in the industry classification used by the Bureau of Economic Analysis. For these reasons, we report the results using national GDP (see Table A2). Although national GDP cannot capture the variation in economic conditions at the state level, it is available and consistently estimated for the entire sample period 1977-2013. The robustness of the results suggests that the time inconsistency affecting the estimation of state-level GDP does not play a role in our analysis. The results are also not sensitive to the inclusion of additional proxies for economic activity. For example, both GDP and the unemployment rate are used to measure economic activity in Table A3. Further, in Table A4 we assume that all states share a common linear time trend. The results are also not sensitive to this assumption.

Fourth, we conduct a sensitivity analysis and estimate equation 1 using weighted least squares. States are weighted by their population size. Thus, we give less weight to smaller states, which may suffer from a larger measurement error. The results are reported in column 2 of Table A5. We also estimate equation 1 assuming that error terms are heteroskedastic within panels (column 3) or correlated across states (column 4). To facilitate the comparison, column 1 reports the base estimates assuming homoskedasticity, no correlation across states but correlation within states. The results are stable.

Table A1: Sensitivity analysis - Contemporaneous correlations between GDP and inequality excluding recent years

	Corr(Gini earnings,Y)		**Corr(Gini wages,Y)**		**Corr(Gini hours,Y)**	
	1967-2006	1977-2006	1967-2006	1977-2006	1967-2006	1977-2006
All	-0.28	-0.43	-0.14	-0.19	-0.43	-0.52
Males	-0.17	-0.35	-0.11	-0.19	-0.36	-0.40
Employed males	-0.01	-0.20	-0.01	-0.18	-0.25	-0.21
	Corr(P90/P50,Y)		**Corr(P90/P10,Y)**		**Corr(P50/P10,Y)**	
	1967-2006	1977-2006	1967-2006	1977-2006	1967-2006	1977-2006
Employed males	-0.06	0.05	0.06	-0.12	0.10	-0.18

Table A2: Sensitivity analysis - National GDP

Dependent variable:			$\ln(\text{Gini}_{s,t})$		
	(1)	(2)	(3)	(4)	(5)
$ln(NGDP_{s,t-1})$	-0.49***	-0.45***	-1.78***	-1.77***	-1.28***
	(0.03)	(0.03)	(0.17)	(0.17)	(0.16)
$School_{s,t-1}$			-1.07***	-1.06***	-0.73***
			(0.12)	(0.12)	(0.12)
$ln(NGDP_{s,t-1}) \times School_{s,t-1}$			0.12***	0.12***	0.08***
			(0.01)	(0.01)	(0.01)
$Population_{s,t-1}$				0.49	0.76
				(0.82)	(0.85)
$Participation\ rate_{s,t-1}$					-0.39***
					(0.05)
Marginal effect of ln(NGDP) at School=					
10 years of schooling			-0.62***	-0.62***	-0.47***
11 years of schooling			-0.51***	-0.51***	-0.39***
12 years of schooling			-0.39***	-0.39***	-0.31***
13 years of schooling			-0.27***	-0.28***	-0.23***
14 years of schooling			-0.16***	-0.16***	-0.15***
15 years of schooling			-0.04	-0.05	-0.07
Linear time trend	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓
State fixed eff. × time trend	✓	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836	1,836
R-squared	0.74	0.75	0.78	0.78	0.79

NGDP refers to national GDP. Population is in hundreds of millions. Robust standard errors (clustered at the state level) are in parentheses. All specifications include a constant term. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Sensitivity analysis - Controlling for the unemployment rate

Dependent variable:	$\ln(\text{Gini}_{s,t})$			
	(1)	(2)	(3)	(4)
$ln(GDP_{s,t-1})$	0.004	-0.44***		
	(0.02)	(0.10)		
$ln(GDP_{s,t-1}) \times School_{s,t-1}$		0.03***		
		(0.01)		
$ln(NGDP_{s,t-1})$			0.04	-0.98***
			(0.04)	(0.14)
$ln(NGDP_{s,t-1}) \times School_{s,t-1}$				0.09***
				(0.01)
$Unemployment\ rate_{s,t-1}$	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
$School_{s,t-1}$	-0.01	-0.40***	-0.01	-0.78***
	(0.01)	(0.09)	(0.01)	(0.09)
$Population_{s,t-1}$	2.23	2.32**	2.27	1.03
	(1.53)	(1.11)	(1.50)	(0.67)
$Participation\ rate_{s,t-1}$	-0.54***	-0.48***	-0.56***	-0.39***
	(0.05)	(0.05)	(0.05)	(0.05)
Linear time trend	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓
State fixed eff. × Time trend	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836
R-squared	0.81	0.81	0.81	0.82

NGDP refers to national GDP, where GDP is state-specific GDP. All regressions include a constant term. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Sensitivity analysis - Common time trend

Dependent variable:	ln($Gini_{s,t}$)				
	(1)	(2)	(3)	(4)	(5)
$ln(GDP_{s,t-1})$	-0.01	-0.02	-0.37***	-0.35***	-0.25***
	(0.02)	(0.02)	(0.08)	(0.08)	(0.05)
$School_{s,t-1}$		-0.06***	-0.36***	-0.33***	-0.21***
		(0.01)	(0.07)	(0.08)	(0.05)
$ln(GDP_{s,t-1}) \times School_{s,t-1}$			0.03***	0.03***	0.02***
			(0.01)	(0.01)	(0.00)
$Population_{s,t-1}$				0.23	0.16
				(0.19)	(0.14)
$Participation\ rate_{s,t-1}$					-0.78***
					(0.06)
Marginal effect of ln(GDP) at School=					
10 years of schooling			-0.10***	-0.10***	-0.07***
11 years of schooling			-0.07***	-0.07***	-0.05***
12 years of schooling			-0.04**	-0.05**	-0.04**
13 years of schooling			-0.02	-0.02	-0.02
14 years of schooling			0.01	0.004	-0.003
15 years of schooling			0.04	0.03	0.02
Linear time trend	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836	1,836
R-squared	0.60	0.62	0.65	0.65	0.74

Population is in hundreds of millions. Robust standard errors (clustered at the state level) are in parentheses. All specifications include a constant term and assume that the time trend is common across states. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Sensitivity analysis - Heteroskedasticity and panel corrected standard errors

Dependent variable:	Earnings inequality $\ln(\text{Gini}_{s,t})$			
	Clustered std. errors	WLS	Het. within panels	PCSE
	(1)	(2)	(3)	(4)
$ln(GDP_{s,t-1})$	-0.66***	-0.66***	-0.66***	-0.69***
	(0.11)	(0.07)	(0.07)	(0.10)
$ln(GDP_{s,t-1}) \times School_{s,t-1}$	0.04***	0.04***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
$School_{s,t-1}$	-0.50***	-0.51***	-0.50***	-0.52***
	(0.09)	(0.06)	(0.06)	(0.10)
$Population_{s,t-1}$	3.04*	3.46***	3.04***	5.29***
	(1.58)	(0.71)	(0.51)	(1.02)
$Participation\ rate_{s,t-1}$	-0.61***	-0.61***	-0.61***	-0.38***
	(0.06)	(0.04)	(0.04)	(0.06)
Linear time trend	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓
State fixed eff. × time trend	✓	✓	✓	✓
Observations	1,836	1,836	1,836	1,836
R-squared	0.78	0.78	0.78	0.96

All regressions include a constant term. WLS refers to weighted least squares, Het. refers to heteroskedasticity, PCSE refers to panel-corrected standard errors. *** p<0.01, ** p<0.05, * p<0.1.