Human Capital, Business Cycles and Labor Supply Volatility

by

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ABSTRACT

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This doctoral thesis investigates the effect of business cycles on individuals decisions, with an emphasis on human capital accumulation. The first chapter shows that low-productivity individuals take advantage of the education sector during a recession by substituting schooling for work and accumulating more human capital. Whereas, high-productivity individuals face a lower unemployment rate and earn a higher labor income. Therefore, they are less likely to leave the labor market and accumulate more human capital. By using survey data from the Current Population Survey, I confirm that this was the case in the US for the period 1986-2011.

The findings of the first chapter have important implications on the volatility puzzle in Real Business Cycle models. One of the shortcomings of these models is the inability to correctly predict the volatility of hours worked. Specifically, the volatility is lower than empirical estimates. The second chapter shows that it is possible to improve the ability of the model to predict labor supply volatility by modeling heterogeneity in productivity. Further, previous papers in the literature find that education can explain the volatility puzzle in a representative-agent setting. I show that this is no longer the case once heterogeneity is introduced in the model and agents face a finite lifetime.

The third chapter focuses on the empirical relationship between business cycles and post-secondary education using Canadian data. The cyclicality of schooling decisions has been extensively analyzed in the literature by using US data. However, there are no studies on the Canadian economy. Main results show that university enrollment is counter-cyclical. Ability, proxied by parental education, negatively affects the counter-cyclicality of university enrollment. Further, economic downturns stimulate the acquisition of theoretical rather than practical education. In fact, contrary to university enrollment, college enrollment is pro-cyclical and enrollment in other (non-university) PSE institutions is acyclical. Finally, macroeconomic conditions mainly affect decisions of recent high-school graduates. Workers are not likely to return to school during recessions.

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The business cycle human capital accumulation nexus: theory and evidence

1.1 Introduction

Among US high-school students age 16 to 24 who graduated in 2009, 70.1% enrolled in college in October 2009. This is the historical high for college enrollment rate since 1959. At the same time, the unemployment rate reached a level of 10% in October 2009 which is also the maximum level for unemployment in the recent financial crisis[1]. This seems to be consistent with several studies in the literature regarding the cyclicality of schooling

[1]Source: US Bureau of Labor Statistics.

decisions. Enrollment in post-secondary education (PSE), in fact, is mainly affected by opportunity costs and financial costs of education. These, in turn, are affected by business cycle fluctuations. On one hand, during a recession, high unemployment decreases the opportunity cost of education and people substitute school for work. On the other hand, family income is lower and students may not be able to afford the cost of education (Christian, 2007). If liquidity constraints are not too tight, the first effect dominates and enrollment is counter-cyclical. This is more likely to happen in OECD countries compared to non-OECD countries (Sakellaris and Spilimbergo, 2000).

From a theoretical point of view, several macroeconomic models have been developed to study the counter-cyclicality of human capital accumulation. Canton (2002), for example, used a discrete time stochastic version of the endogenous growth model developed by Lucas (1988) and Uzawa (1965). He showed that uncertainty leads agents to accumulate more human capital to compensate for future income losses. DeJong and Ingram (2001), instead, developed a Real Business Cycle (RBC) model with skill acquisition. In the presence of a positive TFP shock, human capital is more expensive than physical capital. Thus agents decrease study hours and accumulate less human capital. Within an overlapping generations framework, Heylen and Pozzi (2007) proved that the optimal amount of education depends negatively on the ratio between current and future real wage. Since this ratio is more likely to decrease during recessions, investment in education is counter-cyclical.

Empirically, the results are more controversial. Mattila (1982), Polzin (1984), Kane (1994) and Edwards (1976) found no impact of business cycles on enrollment decisions.

Betts and McFarland (1995), Dellas and Sakellaris (2003), and Dellas and Koubi (2003) found evidence in favor of counter-cyclicality. Finally, Sakellaris and Spilimbergo (2000) found a positive relationship between GDP growth and enrollment rates in non-OECD countries, and a negative relationship in OECD countries.

The cyclicality of schooling decisions has received particular attention in the literature because of its interesting implications. Economic downturns have negative consequences on the economy. However, if enrollment rates are counter-cyclical, then economic crises are also the most efficient time to accumulate human capital and produce more skilled workers. This chapter further investigates the relationship between economic crises and human capital accumulation by focusing on heterogeneity among agents.

This is the first theoretical and empirical study that analyzes the impact of business cycles on enrollment decisions by age and productivity type. In the existing literature, the only paper that looked at heterogeneity among agents in this context is Christian (2007), who distinguished between low and high income individuals. Using data from the October Supplement of the Current Population Survey (CPS), he found that enrollment decisions are more pro-cyclical for low income individuals compared to high income individuals.

Specifically, I embed a Ben-Porath (1967) model of human capital accumulation into a life-cycle RBC setting. This analysis most closely resembles the work of Hansen and İmrohoroğlu (2009), but I build on their work by incorporating an additional type of heterogeneity. I model heterogeneity in learning ability both within and between ages. Moreover, in contrast to their paper, my focus is on formal education rather than learning by doing or on-the-job training.

Results show that business cycles impact different types of agents in different ways. Education is counter-cyclical, but this is especially true for young and low-productivity individuals. Since it is cheaper for them to leave the labor market and go to school, they are more likely to enroll in post-secondary education during an economic downturn. In contrast, high-productivity agents and experienced workers earn higher wages and are less likely to substitute schooling for work. These results are confirmed empirically using US data from the Current Population Survey. Further, the model is able to replicate the empirical regularity that labor supply is more volatile for low-productivity individuals.

The rest of the chapter is organized as follows. The model is presented in Section 1.2. The theoretical results and the business cycle properties of the model are discussed in Section 1.3. The model's predictions regarding the cyclicality of human capital investments are tested empirically using US data in Section 1.4. Finally, Section 1.5 concludes by summarizing the main results.

1.2 The Model

Every year a new generation of equal size is born. Agents face an uncertain life span and may live for a maximum of S_{max} periods. In each period, they are endowed with one unit of time they can allocate among leisure, work and school. Conditional on survival, they must retire at age S_r. During retirement, labor supply and education are absent, and the time endowment is completely allocated to leisure. In any period, there are two types of capital: physical and human capital. Physical capital is accumulated during life through investment, while the human capital stock increases by allocating time to education. Agents start their life with no physical capital and leave no bequests at the end of their life. The initial human capital stock, instead, is positive. This is due to the fact that period 1 in the model represents the 20-year-old cohort in reality. Therefore, the positive initial human capital stock captures the amount of human capital accumulated during mandatory education.

At the beginning of their life, agents maximize their expected lifetime utility:

$$\sum_{s=1}^{S_{max}} \left(\prod_{j=0}^{s-1} \varphi_j \right) \beta^{s-1} \left[\frac{\left(c_{s,t} m_{s,t}^{\gamma} \right)^{1-\eta}}{1-\eta} \right], \tag{1.1}$$

by choosing consumption, investment in human and physical capital, and time spent working and studying. The subscripts *t* and *s* refer to time period and age, respectively. Further, φ_j is the probability of surviving from age j to age $j+1$, β is the discount factor, c is consumption, m is leisure, γ is the disutility of non-leisure activities (i.e. working and studying), and η is the coefficient of relative risk aversion.

The cohort shares, θ_s, are constant over time and are determined by the survival probabilities $\{\varphi_j\}_{j=1}^{S_{max}}$: $\theta_s = \varphi_{s-1}\theta_{s-1}\,(s = 2, .., S_{max})$ and $\theta_1 = 1 - \sum_{s=2}^{S_{max}} \theta_s$, such that the sum of the shares is equal to one.

During the working period, the sources of income are labor and asset wealth accumulated from investment in physical capital. Labor income, in turn, depends on efficiency units of labor $n_{t,s}h_{t,s}$. Individuals can work and study at the same time during their working life. In the retirement period, instead, agents receive a public pension and interest on the investment in physical capital. If an agent survives until age S_{max}, she consumes her entire wealth during the last period. However, if the agent dies earlier, the government collects her assets and redistributes them equally among the surviving agents. Therefore, the budget constraints are given by the following equations:

$$\begin{aligned}
k_{t+1,s+1} &= (1+r_t-\delta)k_{t,s} + (1-\tau_t)w_t n_{t,s} h_{t,s} - \Delta e_{t,s} - c_{t,s} + tr_t && \text{for s} = 1, ..S_r - 1 \\
k_{t+1,s+1} &= (1+r_t-\delta)k_{t,s} + b_t - c_{t,s} + tr_t && \text{for s} = S_r, ..S_{max} - 1, \\
c_{t,s} &= (1+r_t-\delta)k_{t,s} + b_t + tr_t && \text{for s} = S_{max},
\end{aligned} \tag{1.2}$$

where k is physical capital, h is human capital, n is labor supply, e is time spent in education, r is the rental rate of physical capital, δ is the physical capital depreciation rate, w is the wage rate, τ is the tax on labor income, b is the annual public pension benefit level, Δ is the unit cost of education and tr is the government transfer of assets from deceased agents to surviving agents. In the baseline version of the model, Δ is set to zero. Section 1.3.3 shows how the results are affected by the introduction of an education cost.

Within the same cohort, individuals are heterogeneous because of different levels of productivity in learning: high (H) and low (L). The fractions of high and low types are denoted by ξ and $1-\xi$, respectively. On average, high types are more productive in learning compared to low types. Therefore, they can accumulate more human capital given the same amount of time spent in education, e. In particular, human capital accumulation follows:

$$h_{t+1,s+1} = (1-\delta_h)h_{t,s} + \Omega_{s,i}h_{t,s}e_{t,s}^{\phi_i}, \tag{1.3}$$

where $i = \{H, L\}$. The parameter ϕ_i determines how many units of time spent in education effectively contribute to human capital accumulation. This is to capture the quality of education (e.g. number of books in the university library, the student/teacher ratio and the number of laboratories in the university). This parameter may depend on i if high types are more able to take advantage (in terms of human capital accumulation) of the quality of education compared to low types. Later ϕ_i will be calibrated so that the model is consistent with the empirical evidence on household time allocation. Since household time allocation varies by type, so will ϕ. Nonetheless, a sensitivity test will be performed to show how sensitive the results are to the adoption of a common ϕ value. Further, δ_h is the depreciation rate of human capital, and $\Omega_{s,i}$ refers to the productivity in learning which depends on both age *s* and type i. In particular, the productivity in learning declines as the agent becomes older because of the negative impact of aging on learning abilities. Although $\Omega_{s,i}$ refers to the productivity in learning, it also indirectly affects the productivity at work. In fact, a higher productivity in learning implies that agents will acquire more human capital over their life cycle, and therefore they will be more efficient at work.

I assume there is no learning by doing or on-the-job training. Thus, individuals acquire human capital through education only. Moreover, education does not have a direct impact on utility. Agents invest in education only to increase their human capital stock and earn a higher labor income. For this reason, in the retirement period there is no incentive to spend time in education and accumulate human capital, which progressively depreciates as the agent becomes older.

The production sector is given by competitive firms that produce output using efficiency units of labor L_t and physical capital K_t. The production function for the representative firm is Cobb-Douglas:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1.4}$$

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 are equal to the marginal products:

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

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

Finally, the government collects labor income taxes, τ_t, from the workers and provides public pensions, b_t, to the retired agents using a pay-as-you-go system. Public expenditure must be completely financed by tax revenue in every period:

$$\tau_t w_t L_t = b_t \textstyle\sum_{s=S_r}^{Smax} \theta_s.$$

1.2.1 Competitive equilibrium

Given the government policy (b_t and τ_t), 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:

1. The individual policy rules solve the household's maximization problem.

2. Prices $\{w_t, r_t\}$ solve the representative firm's maximization problem.

3. The government balanced-budget constraint is satisfied.

4. The market-clearing condition is satisfied:

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

5. Individual decisions are consistent with aggregate outcomes:

$$L_t = \textstyle\sum_{s=1}^{S_r-1} \left(n_{s,t,H} h_{s,t,H} \xi + n_{s,t,L} h_{s,t,L} (1-\xi)\right) \theta_s,$$

$$K_t = \textstyle\sum_{s=1}^{S_{max}} \left(k_{s,t,H} \xi + k_{s,t,L} (1-\xi)\right) \theta_s.$$

1.2.2 Calibration

The calibration is target to US data and it is consistent with the standard practice in the RBC literature. One model period corresponds to one year in reality. The calibrated values are reported in Table 1.1. In particular, survival probabilities are from Bell and Miller (2002). S_{max} is set to 58 years in order to match the life expectancy at age 20 of males born in 1960 estimated by Bell and Miller (2002). S_r is set to 43 to target the ratio of retired people to total active population estimated from 1990 Population Census. The fraction of high types, ξ, is set to 0.58. This is the average fraction of high-school students that enrolled in colleges and universities for the period 1962-2012 (Bureau of Labor Statistics). I experimented with other values for ξ as well. However, the properties of the model are qualitatively the same.

The discount factor and the depreciation rate of physical capital are set to 0.9434 and 6%, respectively, so that in the model the average physical capital to output ratio is 3 and the average annual real interest rate is 6%. These values imply a capital share of output of 0.36. The disutility of non-leisure activities, γ, is chosen to target the average time spent working to 0.33. The replacement ratio of pension benefits is set to 43% in order to match the social security payroll tax rate in US (i.e. 10.7% from Conesa and Krueger, 1999). The parameters for the Solow residual are chosen to be $\rho =$0.814 and $\sigma =$0.0142. These parameters are equivalent to the values estimated by Prescott (1986) for quarterly frequencies[2]. Finally, the risk aversion parameter, η, is set to target US output volatility. The calibrated value is within the range of values commonly used in the literature, $\eta \in (1, 3)$.

Regarding the human capital accumulation function, three parameters must be cali-

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

brated: the depreciation rate of human capital δ_h, the parameter ϕ_i, and the productivity sequence $\Omega_{s,i}$. There is no agreement in the literature about the depreciation of human capital. Estimates vary from 0.5% to 4.7%[3]. All values in this range generate results that are qualitatively the same. However, by setting $\delta_h = 0.5\%$ the model is more able to replicate the empirical profile for study hours. For this reason, the results presented in Section 1.3 are based on $\delta_h = 0.5\%$. Figure 1.1 reports the profiles for time spent in education for other values.

The parameter ϕ_i, instead, is calibrated to target the average time spent in education over the working period, e^*, estimated using data from the "American Time Use Survey" (ATUS, 2003-2011). e^* is the average time spent for taking classes and doing homework/research necessary to pursue a degree or a certification, and it is computed as a fraction of the total available time (i.e. 24 hours/day). Since e^* is affected by the productivity in learning, one value of ϕ is estimated for each ability type. Empirically, ability types are defined based on educational achievement. In particular, an individual is considered to be a high type if she has received a college degree or if she is currently attending college. This includes college students and individuals with a college degree, Bachelor's degree, Master's degree, professional school degree or Doctoral degree. Low types, instead, have at most an associate degree from a non-academic program (i.e. vocational/professional program). This includes individuals with less than high school, with a high school diploma, with an associate degree from a non-academic program, and individuals who attended college in

[3]Estimates of the human capital depreciation rate vary within 1%-3.4% in Johnson and Hebein (1974), 0.5%-4.3% in Haley (1976), 0.7%-4.7% in Heckman (1976).

the past but did not graduate. Based on this classification, the estimated average time spent studying is equal to 0.017 for high types and 0.002 for low types.

The productivity sequence is calibrated using the human capital accumulation function[4]:

$$\Omega_{s,i} = \frac{h^*_{s+1,i} - (1-\delta_h)h^*_{s,i}}{h^*_{s,i} e_s^{i*\phi_i}}, \tag{1.5}$$

where $e^*_{s,i}$ is the average time spent studying for each age *s* and ability type, and it is computed using annual data from ATUS. The efficiency weights $h^*_{s,i}$, instead, are calibrated following the methodology proposed by Hansen (1993) and using data on hourly earnings from the Panel Study of Income Dynamics (PSID) 1967-2008[5]. It is worth mentioning that Hansen (1993) did not distinguish between high and low types. His methodology produces one sequence of h^*_s for the whole economy. However, the procedure has been extended in order to distinguish between ability types, which are empirically defined as before. In particular, averages of $e^*_{s,i}$ and $h^*_{s,i}$ are first obtained for five age groups (20-24, 25-34, 35-44, 45-54, 55-62) and the two productivity types. These values are then interpolated[6] to obtain one value for each age and type. The sequence for $h^*_{s,i}$ is also used to calibrate the initial levels of human capital for high and low types[7].

Figure 1.2 shows the estimated efficiency weights, $h^*_{s,i}$, and the productivity sequence,

[4]In order to obtain a series for $\Omega_{s,i}$, a value for ϕ_i is required first. Starting from an initial guess of ϕ_i, I generate a series for $\Omega_{s,i}$ and then run a simulation to obtain a profile for e^i_s. If the average time devoted to education does not match the data (i.e. 0.017 for high types and 0.002 for low types), the guess for ϕ_i is updated until convergence.

[5]Data for hourly earnings are missing for the following years: 1992, 2003, 2005 and 2007. Hourly earnings are converted in 1967 constant dollars.

[6]Specifically, I use polynomial interpolation of third degree.

[7]$h_{1,H}$=0.5758 and $h_{1,L}$=0.5730.

$\Omega_{s,i}$, during the working life. In particular, the efficiency at work increases when agents are young, has a peak around the middle age and then it starts to decline. Further, at any age high types are more efficient at work than low types. The productivity in learning, instead, determines the human capital stock each agent can accumulate given the stock previously acquired and the amount of time spent in education. Clearly, this depends on age. In particular, the productivity decreases as the agent becomes older because of the negative impact of aging on learning abilities. Further, the productivity is higher for high types until age 40. In fact, the difference in productivity between the two types decreases as individuals age. After age 40, there is no significant difference between the two types.

1.2.3 Solution method

The non-stochastic steady state (i.e. $z^* = 1$) in the 58-period Overlapping Generations model has been computed using a guess and verify method. The algorithm can be summarized as follows. Firstly, I guess the steady-state aggregate values for labor in efficiency units and physical capital. Secondly, I compute the factor prices and the tax rate, and solve the household maximization problem for the two ability types by using backward induction. Thirdly, I compute the aggregate values for labor in efficiency units and physical capital. Finally, the initial guesses are updated using the computed aggregate values and the procedure is repeated until convergence.

In order to analyze the effect of business cycles on human capital accumulation, a negative technology shock has been introduced in the model. The transitional dynamics are computed by log-linearizing the first order conditions around the non-stochastic steady state. The impulse response functions are then obtained to describe the dynamics that lead the economy to the steady state after the shock. The results are discussed in the next section.

1.3 Results

The non-stochastic steady state is described in Table 1.2. Figure 1.3, instead, shows the steady-state levels for the main variables by age and productivity type. Since high types are more productive in learning compared to low types, they spend more time in education and accumulate more human capital in the steady state. Further, at the beginning of their life, they work less and borrow more physical capital to finance education. Although the cost of education is excluded in this part of the analysis, an agent must spend less time working and forgo part of her labor income in order to study. Therefore, the young high-type borrows physical capital to smooth consumption over time. Around age 25, the time spent studying is significantly reduced and the agent starts to invest in physical capital.

Figure 1.4 shows the ability of the model to match the empirical life-cycle profiles for both types for hours worked, time spent in education, wages and the growth rate of efficiency units. Data on time spent studying are from ATUS 2003-2011. Data on wages and hours worked are from PSID 1967-2008[8]. Further, the wage profiles have been computed taking into account time effects following the methodology in Huggett et al. (2011). Since

[8]Data about hours worked are missing for the following years: 1992-2000.

hours worked and wages have different units in the model and in the data, they have been normalized to 1 at age 20. Efficiency units are estimated as discussed in Section 1.2.2. The overall performance of the model is good. However, there are some discrepancies in wages and hours worked, especially later in the life cycle. This can be explained by the fact that the productivity in learning is very low in the model after age 30. The incentive to study is reduced. Thus, agents stop accumulating human capital, which starts to decrease at rate δ_h. This leads to a decline in efficiency wages and, therefore, hours worked in the model. However, these declines are not observed in the data. The discrepancy could be explained by the fact that the model does not include some features of the data that prevent wages and hours from falling (e.g. unions and indivisibilities in labor time). Nevertheless, the model is able to replicate the empirical fact that, on average, hours worked are increasing in skills. This fact is documented in Kydland (1984) and it is confirmed in the PSID sample used to calibrate the model. In the data, low types spend 31.5% of their time working, while high types allocate 34% of their time to work. The percentages produced by the model are 30% and 35.5%, respectively.

In order to analyze how agents' decisions are affected by business cycles, a negative one-standard deviation technology shock has been introduced in the model. Figure 1.5 shows the impulse response functions for the aggregate economy. The graphs represent the percent deviation of each variable from the steady state after the shock. The curves show that physical capital, investment, consumption and hours worked are pro-cyclical. Time spent in education, instead, is counter-cyclical. In particular, when the economy is hit by a negative technology shock, the marginal products of labor and physical capital decrease. Thus, both wage and rental rate of physical capital drop initially. Agents invest less in physical capital and reduce hours worked. Output and consumption decrease. Further, individuals invest more in education to accumulate more human capital and compensate for the reduction in labor income due to the wage contraction. This is manly due to the decrease in the opportunity cost of education. During a downturn, in fact, the decrease in the wage rate reduces the opportunity cost of education. Individuals substitute time spent studying for time spent working. As a consequence, human capital accumulation increases in contrast with the decrease in physical capital accumulation. Agents substitute human capital for physical capital because the shock reduces the rate of return to physical capital investments compared to the rate of return to human capital investments. This result is consistent with findings in DeJong and Ingram (2001). Therefore, the education sector acts as a buffer sector. In particular, it allows agents to compensate for the reduction in labor income by increasing the human capital stock. However, as human capital increases, its marginal product decreases. After approximately ten periods agents start to substitute back physical capital for human capital and the economy starts to converge to the original steady state.

1.3.1 Differences by ability type and age

Figures 1.6 and 1.7 show the impulse response functions for education and labor supply, respectively, by age and productivity type. In both figures, the top left graph shows the behavior of the average high and low type. The other graphs show the impulse response functions for three age groups: 20-24, 25-34 and 35-62 years of age. Time spent in education is more counter-cyclical for low types rather than high types. Accordingly, the reduction in labor supply is stronger for low types. This is due to the fact that, on average, high-productivity agents have already accumulated a large amount of human capital before the crisis. They are more efficient at work and earn a higher labor income. Therefore, it is more expensive for them to reduce hours worked and forgo labor income in order to study and accumulate more human capital. Further, the marginal product of human capital is relatively low for high types. Thus, they benefit less by substituting human for physical capital. However, there is no significant difference between ability types when individuals are in the age group 35-62. This is due to the fact that the difference in Ω decreases as agents become older.

Moreover, the deviation of time spent in education decreases with age. The reason is twofold. Firstly, older agents have accumulated a higher steady-state human capital stock during their working life. Thus, they are more productive at work and less willing to reduce hours worked and accumulate extra human capital. Secondly, the marginal product of human capital and, therefore, the benefit from studying are lower for them. Regarding labor supply, the deviation from the steady state is larger for young and old agents, compared to middle age agents.

These results are consistent with what can be observed in reality. During a crisis, labor market conditions are worse: it is harder to find a job or receive a high labor income.

However, certain categories of individuals are more affected than others. In particular, young and low-productivity individuals face even harder labor market conditions. Young people do not have experience in the labor market yet. Low types are less efficient at work than high types because, on average, they accumulate less human capital. Therefore, when the crisis hits the economy, these categories benefit more from the education sector and the substitution between physical and human capital.

These results suggest that different individuals in the economy react differently to business cycles. In particular, the labor market response to shocks is heterogeneous. Taking into account this heterogeneity may be especially important for stabilization policies. Representative-agent models can only determine the impact of policies on the average person in the economy. However, the impact on other individuals may be very different. The results in this chapter suggest that it may be important to take into account heterogeneity among agents.

1.3.2 Business cycle statistics

Table 1.3 shows the average business cycle statistics computed from 500 simulations[9] of the life-cycle RBC model, along with annual business cycle statistics from US data. The data about labor supply are from CPS, March Supplement (1962-2012). Hours worked are obtained using the answer to the question “How many hours did you actually work

[9] Each simulation consists of 100 periods.

last week?”[10]. Data for output, consumption and investment are from US Bureau of Economic Analysis (1962-2012). Output is measured by real GDP, consumption by personal consumption expenditures and investment by gross private domestic investment. Both the actual and the simulated series are transformed by taking natural logarithms and detrended using the Hodrick-Prescott filter. Following Ravn and Uhlig (2002), the smoothing parameter is set to 6.25. It is worth mentioning that there are not enough data to produce business cycle statistics for time spent in education. ATUS is only available starting from 2003. However, the ability of the model to match the empirical evidence regarding the education sector is analyzed in the next section.

The model underestimates the volatility of labor supply and consumption. However, it is able to replicate a U-shaped volatility profile (i.e. higher volatility for young and old agents compared to middle age agents) consistent with the data. Further, the model is able to predict a higher volatility for low types compared to high types. This empirical regularity is also documented in Ríos-Rull (1993): the volatility of hours worked is decreasing in skills. Heterogeneity in productivity generates differences among agents in terms of the cost of reducing hours worked. Reducing hours worked is cheaper for agents with a lower human capital stock because they give up a lower labor income. Therefore, when the shock hits the economy, these agents reduce hours worked more and their volatility increases. Moreover, low types are more likely to substitute work with schooling during economic

[10] To compute business cycle statistics about labor supply, CPS is preferred to PSID because it has significantly more observations and it is available for a longer period of time. Further, it has information about ”actual” hours worked as opposed to ”usual” hours worked. The former is preferred because usual hours worked mainly reflect the number of hours reported in the work contract (which could be different than the actual hours) and, therefore, tend to be less volatile than actual hours worked.

downturns. For these reasons, their labor supply volatility is higher compared to that of high-ability agents. To the best of my knowledge, this is the first paper that is able to replicate this empirical regularity.

Finally, in order to test the robustness of the findings to the parameter ϕ, I have solved the model when ϕ is the same for both ability types. Table 1.4 reports the calibrated parameters for this alternative specification. All parameters are re-calibrated following the procedure described in Section 1.2.2 with the exception of ϕ, which is now set to match the average time spent studying for the aggregate economy. This statistics is obtained from ATUS (2003-2011) and it is equal to 0.007. Figures 1.8 and 1.9 show the impulse response functions for the main variables of interest, while Table 1.5 reports the business cycle statistics. The results are not significantly affected by this change. In fact, the findings previously discussed are driven by the productivity in learning, Ω, rather than the exponent ϕ. However, it is necessary to use different ϕ values for the two ability types in order to match the empirical life-cycle profiles for time spent studying, as shown in Figure 1.10. For this reason, the preferred specification distinguishes between ϕ_H and ϕ_L.

1.3.3 The cost of education

This section investigates how the explicit cost of education affects the model's predictions. In particular, Figure 1.11 shows the impulse response functions of education when the cost, Δ, is positive. Specifically, this parameter is set to 0.5 to match annual aggregate tuition and fees (charged for full-time students in degree-granting post-secondary institutions) over GDP for the period (1969-2012). Data on tuition and fees are from the Digest of Education Statistics. All other parameters are the same as in the baseline model with no education cost.

As shown in Figure 1.11, both the volatility and the counter-cyclicality of education decrease as the cost of education increases. Since education is more expensive, schooling is less appealing than before. However, education is always more counter-cyclical for low types compared to high types. Therefore, the results discussed in previous sections are robust to the introduction of an explicit cost of education.

Further, although the model with Δ=0.5 is able to match data on aggregate tuition, it may not necessarily match education expenditure at the individual level. In reality, students may be subsidized by their parents or the government. Therefore, they may not directly pay for education. The two versions of the model, with and without education cost, represent two extreme cases: students pay the entire cost of education or not at all. Although the results are very similar, the preferred specification is the model without education cost. Since this specification produces a lower labor supply volatility, setting $\Delta = 0$ in the baseline model is a conservative choice.

1.4 Empirical Analysis

In this section, the theoretical predictions of the model are tested empirically using US data. Figure 1.12 shows the deviations from the HP trend of GDP and college enrollment rates in US for the period (1986-2011)[11]. The correlation coefficient between the two series is -0.26. Therefore, college enrollment is counter-cyclical, which is consistent with the model's predictions for the aggregate economy.

At the micro level, the theoretical predictions are tested using American survey data from CPS March Supplement (1986-2011) [12]. In particular, the sample consists of 118,618 high-school graduates of age 16 to 24. Table 1.8 reports the mean of the main variables of interest. The cyclicality of schooling decisions has been extensively analyzed in the literature. Although the methodology is quite homogeneous, the results are controversial. Compared to existing papers, this analysis considers a longer time period. Further, it distinguishes between high and low ability individuals. As largely documented in the literature, enrollment rates in post-secondary education are affected by demographics, geography, family resources, parental education and tuition. Given this set of characteristics, the probability of being enrolled is estimated using a probit regression:

$$Pr(enrolled_{it} = 1/X, Z) = \Psi(constant + \alpha X_{it} + \beta Z_t), \tag{1.6}$$

where $enrolled_{it}$ is a dummy variable equal one if individual i is enrolled at time t and zero otherwise[13], Ψ is the standard normal distribution function, X is the vector of control variables and Z is a proxy for business-cycle fluctuations. In the literature, the most

[11] Enrollment rates are from the Bureau of Labor Statistics, GDP is from the Bureau of Economic Analysis. Both series are detrended using an HP filter with smoothing parameter equal to 6.25.

[12] Questions regarding enrollment in post-secondary education are available in CPS starting from 1986 only.

[13] A person is considered to be enrolled if she is attending a full-time or part-time program in a post-secondary institution.

common proxy is unemployment. Instead, I use GDP for consistency with the theoretical model discussed in Section 1.2. However, the results are robust to different measures of business-cycle fluctuations, as reported in Section 1.4.1.

The average marginal effects from the probit estimation are reported in Table 1.9. Robust standard errors, corrected for clustering and stratification, are in parentheses[14]. The main variable of interest is ln(GDP), which has a negative marginal effect. In particular, a one-percent increase in GDP above trend decreases the probability of being enrolled in PSE by 1.37 percentage points. This implies that enrollment rates are counter-cyclical, which is consistent with the theoretical results.

Moreover, the impact of age on enrollment is negative. *Ceteris paribus*, females have a higher probability to be enrolled than males. A non-single person is less likely to enroll in PSE compared to a single person. House ownership positively affects the probability of being enrolled, while family size decreases the likelihood of enrollment. If the head of the household is employed, the probability of college enrollment is higher. A $1,000-increase in the amount received from the Federal Pell Grant Program[15] increases enrollment by 5.5 percentage points. Schooling decisions are also affected by parental education. Note that the omitted category is represented by individuals whose parents completed at least

[14]The information about clustering and stratification variables in CPS is not released to the public. Further, replicate weights are not available before 2005. Therefore, in order to correct the standard errors, I use proxies for clustering and stratification variables. In particular, I define the stratum to be the state in which the individual lives. This is the smallest geographic unit that can be identified in CPS (public version). Households, instead, are used to identify clusters. As robustness check, I compare the standard errors from the estimation with replicate weights and the one with proxies for clustering and stratification variables for the period 2005-2011. Results show that there is no significant difference in the estimated standard errors. See Davern et al. (2006) and Davern et al. (2007) for more details.

[15]This variable indicates the amount of money received from the Federal Pell Grant Program. Pell Grants are limited to college students with financial needs.

one year at any PSE institution. A negative marginal effect implies that an individual is less likely to enroll in college if her/his parents did not go to college. Further, schooling decisions are more affected by father's education than mother's education. Finally, some may be surprised by the positive effect of tuition on enrollment. However, this variable has a double effect. On one hand, higher tuition fees discourage enrollment because the cost of education is higher. On the other hand, tuition is positively related to the quality of education[16]. Therefore, students may be more willing to enroll in costly universities because they have a higher reputation. The positive sign of the coefficient suggests that the second effect dominates.

The sample has also been divided into two "productivity" groups in order to distinguish between high and low types. Parental education is used as proxy for the productivity in learning. In particular, high types are defined as those individuals whose parents studied at least one year at any post-secondary institution. Low types are those individuals whose parents have at most a high-school diploma. The results are presented in columns 2 and 3 of Table 1.9. In particular, a one-percent increase in GDP above trend decreases the probability of being enrolled by 0.66 percentage points for high types and by 1.94 percentage points for low types. This is consistent with the predictions of the theoretical model: the counter-cyclicality is stronger for low-productivity individuals.

Finally, Figure 1.13 shows the average marginal effect of GDP (on the probability of being enrolled in college) by age. In CPS the question about college enrollment is asked

[16] This relationship is observed empirically but it is not incorporated into the theoretical model previously discussed.

to young (age 16-24) individuals only. Therefore, it is difficult to understand whether age affects the counter-cyclicality of education within this age group. To be consistent with the theoretical results, the marginal effect should be increasing in age (going from negative to positive values). A similar pattern can be found in the sub-sample of low types. However, no clear pattern results from the graphs for high types and the aggregate economy.

1.4.1 Sensitivity analysis

Table 1.10 shows the robustness of the results to different proxies of business-cycle fluctuations. The table reports the average marginal effect for each alternative measure. In all cases, enrollment in PSE is counter-cyclical. The variables that are negatively correlated with GDP have a positive marginal effect on the likelihood of being enrolled. In fact, when the national unemployment rate increases by one percentage point, the probability of being enrolled increases by 4.4 percentage points. The impact of state unemployment is lower but still significant. The variables that are positively correlated with GDP, instead, have a negative impact. In particular, the effect of employment is similar in magnitude to the effect of the national unemployment rate. When employment increases by one percentage point, the likelihood of being enrolled decreases by 4.8 percentage points. Further, a one-unit increase in the industrial production index decreases the probability of being enrolled by 0.9 percentage points. Finally, independently of the business cycle measure, the impact is greater for low types compared to high types.

In Table 1.11 the robustness of the results is tested by changing the criterion used to define high and low types. The first column reports the results using the original classification. In the second column, high types are defined as those individuals whose parents have at least obtained a Bachelor's degree. Finally, in the third column, high types are defined as those individuals whose parents have at least completed grade 12. Results suggest that the effect of GDP on enrollment decisions is always stronger for low types. The magnitude of the effects depends on the classification of high and low types, in a way that is consistent with the theoretical predictions from the model.

1.5 Conclusions

This chapter has shown that, during an economic crisis, the education sector helps the economy to react to the income reduction. The decrease in wages reduces the opportunity cost of education, while the decrease in the rental rate of physical capital decreases its marginal product. Therefore, agents invest more in human capital because it is cheaper (therefore more efficient) to do so. Education is less expensive and human capital is more attractive than physical capital. This is especially true for young and low-productivity agents. In fact, since both are less productive at work, they are more likely to substitute schooling for work. These results are empirically confirmed using US data: a one-percent increase in GDP above trend decreases the probability of being enrolled by 1.37%. However, the marginal effect is higher for low types compared to high types. On average, the impact on low types' enrollment decisions is three times higher than that on high types.

These results are robust to alternative specifications and indicators of business cycles fluctuations.

Finally, the model developed in this chapter is able to replicate the empirical regularity that labor supply volatility is higher for low-productivity individuals. This chapter suggests that the cost of reducing labor supply during recessions is lower for low-productivity individuals. Therefore, they are more likely to reduce hours worked and substitute labor with other alternatives. Education seems to be a valid alternative to work, especially for young individuals. However, it is worth mentioning that this does not completely explain the volatility of low types. Other explanations, which are not explored in this chapter, may be related to the demand side of the labor market (i.e. employers may be more likely to lay off low-productivity employees during recessions) or to the fact that low types are more likely to work in sectors severely affected by recessions.

Tables and Figures

Table 1.1: Calibration of the model ($\delta_h = 0.5\%$)

Parameter	Calibrated value	Set to target	Value from US data	Value from the model
S_{max}	58	life expectancy at age 20	57.2	57.5
S_r	43	ratio of retired people to active population	21.6%	21.7%
γ	1.85	n^*	0.33	0.33
η	1.17	σ_Y	1.35	1.35
δ	0.06	average annual real interest rate	6%	6%
β	0.9434	average physical capital to output ratio	3	3
ϕ_H	0.106	e_H^*	0.017	0.017
ϕ_L	0.025	e_L^*	0.002	0.002

Table 1.2: Steady-state aggregate values ($\delta_h = 0.5\%$)

Aggregate values:	C^*	N^*	L^*	K^*	Y^*	w^*	r^*	b	τ^K
	0.35	0.33	0.33	0.74	0.44	0.86	0.12	0.14	0.107

Household problem:	N^*	K^*	H^*	E^*
high type	0.36	0.53	1.13	0.017
low type	0.30	1.03	0.84	0.002

Table 1.3: Business cycle statistics

X	σ_X		$\frac{\sigma_X}{\sigma_Y}$		$corr(X,Y)$	
	Data	Model1	Data	Model1	Data	Model1
Y	1.35	1.35	1	1	1	1
C	1.12	0.45	0.83	0.33	0.91	0.96
I	6.72	10.5	4.98	7.78	0.92	0.98
N	1.26	0.76	0.93	0.56	0.86	0.97
N_L	1.49*	1.16	1.10	0.86	0.85*	0.99
N_H	0.64*	0.47	0.47	0.35	0.77*	0.95
N (20-24)	2.20	0.75	1.63	0.56	0.79	0.98
N (25-34)	1.47	0.54	1.09	0.40	0.83	0.99
N (35-44)	1.07	0.56	0.79	0.41	0.85	0.96
N (45-54)	1.06	0.96	0.79	0.71	0.85	0.84
N (55-62)	1.09	1.26	0.81	0.93	0.77	0.96
N_L*(20-24)*	2.61*	1.10	1.93	0.81	0.76*	0.99
N_L*(25-34)*	1.84*	0.96	1.36	0.71	0.83*	0.99
N_L*(35-44)*	1.49*	0.99	1.10	0.73	0.83*	0.99
N_L*(45-54)*	1.30*	1.17	0.96	0.87	0.87*	0.99
N_L*(55-62)*	1.23*	1.71	0.91	1.27	0.79*	0.99
N_H *(20-24)*	1.43*	0.53	1.06	0.39	0.55*	0.95
N_H*(25-34)*	0.80*	0.33	0.59	0.24	0.78*	0.92
N_H *(35-44)*	0.64*	0.32	0.47	0.24	0.66*	0.92
N_H*(45-54)*	0.72*	0.45	0.53	0.33	0.56*	0.96
N_H*(55-62)*	1.00*	0.86	0.74	0.64	0.37*	0.97

Y is output, C is consumption, I is investment, N is labor supply, N_L is labor supply for low types and N_H is labor supply for high types.* Refers to time period 1992-2012: hours worked for the two ability types can be estimated starting from 1992 only because the question about education achievement in CPS was changed in 1992. Thus, in order to have a definition of ability type consistent over time, N_L and N_H have been estimated using data from 1992 to 2012 only.

Table 1.4: Calibration of the model with a common ϕ value

Parameter	Calibrated value	Set to target	Value from US data	Value from the model
γ	1.82	n^*	0.33	0.33
ϕ	0.055	e^*	0.007	0.007

The remaining parameters are the same as in Table 1.1.

Table 1.5: Business cycle statistics with a common ϕ value

Specification:	Model1	Common ϕ	Model1	Common ϕ	Model1	Common ϕ
X	σ_X		$\frac{\sigma_X}{\sigma_Y}$		$corr(X,Y)$	
Y	1.35	1.34	1	1	1	1
N	0.76	0.77	0.56	0.57	0.97	0.98
N_L	1.16	1.16	0.86	0.87	0.99	0.98
N_H	0.47	0.50	0.35	0.37	0.95	0.94
E	0.54	0.59	0.40	0.44	-0.99	-0.99
E_L	0.75	0.77	0.56	0.57	-0.84	-0.83
E_H	0.39	0.46	0.29	0.34	-0.46	-0.64

Table 1.6: Business cycle statistics with a positive cost of education

COST	0	0.5	0	0.5	0	0.5
X	σ_X		$\frac{\sigma_X}{\sigma_Y}$		$corr(X,Y)$	
Y	1.35	1.40	1	1	1	1
N	0.76	0.89	0.56	0.63	0.96	0.96
N_L	1.16	1.26	0.86	0.90	0.99	0.99
N_H	0.47	0.58	0.35	0.41	0.95	0.97
E	0.54	0.26	0.40	0.19	-0.93	0.18
E_L	0.75	0.40	0.56	0.29	-0.84	-0.33
E_H	0.39	0.17	0.29	0.12	-0.46	0.49

Table 1.7: Data sources

Variable	Source
Unemployment rate:	US Bureau of Labor Statistics
Interest rate:	World Bank
Inflation rate (calculated from CPI)	US Bureau of Labor Statistics
Tuition:	National Centre for Education Statistics
Other controls:	Current Population Survey

Table 1.8: Means of control variables

Variable	Whole sample	High types	Low types
Age	20.5	20.4	20.6
Female	0.49	0.49	0.49
Married	0.01	0.01	0.02
Separated/Divorced/Widowed	0.01	0.01	0.01
Single	0.98	0.98	0.97
College enrollment	0.61	0.73	0.52
Family income	113,227	143,544	91,389
Family size	4.5	4.4	4.5
House ownership	0.89	0.94	0.86
Head of household employed	0.85	0.89	0.82
Resident in metropolitan area	0.76	0.79	0.74
Amount Pell Grant received	1,240	1,619	967
Mother's education $<$ high school	0.18	0	0.31
Mother's education = high school diploma	0.29	0	0.50
Mother's education $>$ high school	0.53	1	0.19
Father's education $<$ high school	0.17	0	0.30
Father's education = high school diploma	0.26	0	0.44
Father's education $>$ high school	0.57	1	0.26

Table 1.9: Average marginal effects from probit estimation

Dependent variable: college enrollment (=1 if enrolled in PSE, =0 otherwise)

	WHOLE SAMPLE		HIGH TYPES		LOW TYPES	
Variable	**dydx**	**(Std. Err.)**	**dydx**	**(Std. Err.)**	**dydx**	**(Std. Err.)**
ln(GDP)	-1.365***	(0.078)	-0.661***	(0.110)	-1.944***	(0.108)
Age	-0.055***	(0.001)	-0.058***	(0.001)	-0.054***	(0.001)
Female	0.071***	(0.003)	0.050***	(0.004)	0.085***	(0.004)
Married	-0.220***	(0.015)	-0.213***	(0.025)	-0.226***	(0.019)
DSW[1]	-0.151***	(0.016)	-0.148***	(0.024)	-0.155***	(0.021)
ln(family income)	0.002	(0.002)	0.017***	(0.003)	-0.006**	(0.002)
ln(family size)	-0.046***	(0.006)	-0.039***	(0.009)	-0.052***	(0.008)
House ownership	0.075***	(0.005)	0.076***	(0.009)	0.075***	(0.006)
Head of HH employed	0.023***	(0.004)	0.013*	(0.008)	0.029***	(0.006)
Metropolitan area	0.038***	(0.005)	0.013*	(0.007)	0.048***	(0.006)
Pell Grant*1,000	0.055***	(0.003)	0.034***	(0.003)	0.074***	(0.006)
Mean weakly earnings*1,000	0.025***	(0.002)	0.014***	(0.003)	0.032***	(0.003)
Tuition*1,000	0.122***	(0.029)	0.128***	(0.043)	0.113***	(0.040)
Nominal interest rate	0.004**	(0.001)	-0.000	(0.002)	0.006***	(0.002)
Inflation	0.023***	(0.002)	0.011***	(0.003)	0.034***	(0.003)
Linear time trend	0.046***	(0.004)	0.015**	(0.006)	0.072***	(0.006)
Mother's education (compared to > high school diploma):						
<high-school diploma	-0.096***	(0.005)			-0.105***	(0.007)
=high school diploma	-0.101***	(0.004)	-	-	-0.089***	(0.006)
Father's education (compared to > high school diploma):						
<high-school diploma	-0.121***	(0.005)	-	-	-0.123***	(0.006)
=high-school diploma	-0.113***	(0.004)	-	-	-0.104***	(0.006)
Observations	118,618		49,668		68,950	

Robust standard errors are reported in brackets. The regression also includes ethnicity dummies and state dummies. There are no estimates for parental education in the high types group because the corresponding dummy variables are equal zero for this group. Average Weakly Earnings refers to earnings in non-agricultural sectors in 1985 constant dollars. Family income, tuition and Pell Grants are in 1985 constant dollars as well. 1. DSW: divorced/separated/widowed.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.10: Robustness to alternative cyclical indicators

Dependent variable: college enrollment (=1 if enrolled in PSE, =0 otherwise)				
	National unemployment rate	State unemployment rate	Index of industrial production	National employment rate
Whole sample	0.044***	0.020***	-0.009***	-0.048***
	(0.002)	(0.001)	(0.001)	(0.002)
High types	0.024***	0.012***	-0.005***	-0.026***
	(0.003)	(0.003)	(0.001)	(0.003)
Low types	0.059***	0.026***	-0.012***	-0.067***
	(0.003)	(0.002)	(0.001)	(0.003)

Robust standard errors are reported in brackets. Each estimation includes the same variables as in Table 1.9. *** p<0.01, ** p<0.05, * p<0.1

Table 1.11: Robustness analysis: ability

Dependent variable: college enrollment (=1 if enrolled in PSE, =0 otherwise)						
	HIGH $>$ high school diploma	LOW $\leq$ high school diploma	HIGH $\geq$ Bachelor's degree	LOW $<$ Bachelor's degree	HIGH $\geq$ Grade 12	LOW $<$ Grade 12
Ln(GDP)	-0.661***	-1.944***	-0.230	-1.428***	-0.829***	-2.16***
	(0.109)	(0.108)	(0.157)	(0.092)	(0.086)	(0.198)
N	49,668	68,950	21,279	97,339	100,639	17,979

Robust standard errors are reported in brackets. Each estimation includes the same control variables as in Table 1.9. Similar results are obtained if using different business-cycle proxies. *** p<0.01, ** p<0.05, * p<0.1

Figure 1.1: Profiles for time spent in education for different levels of δ_h

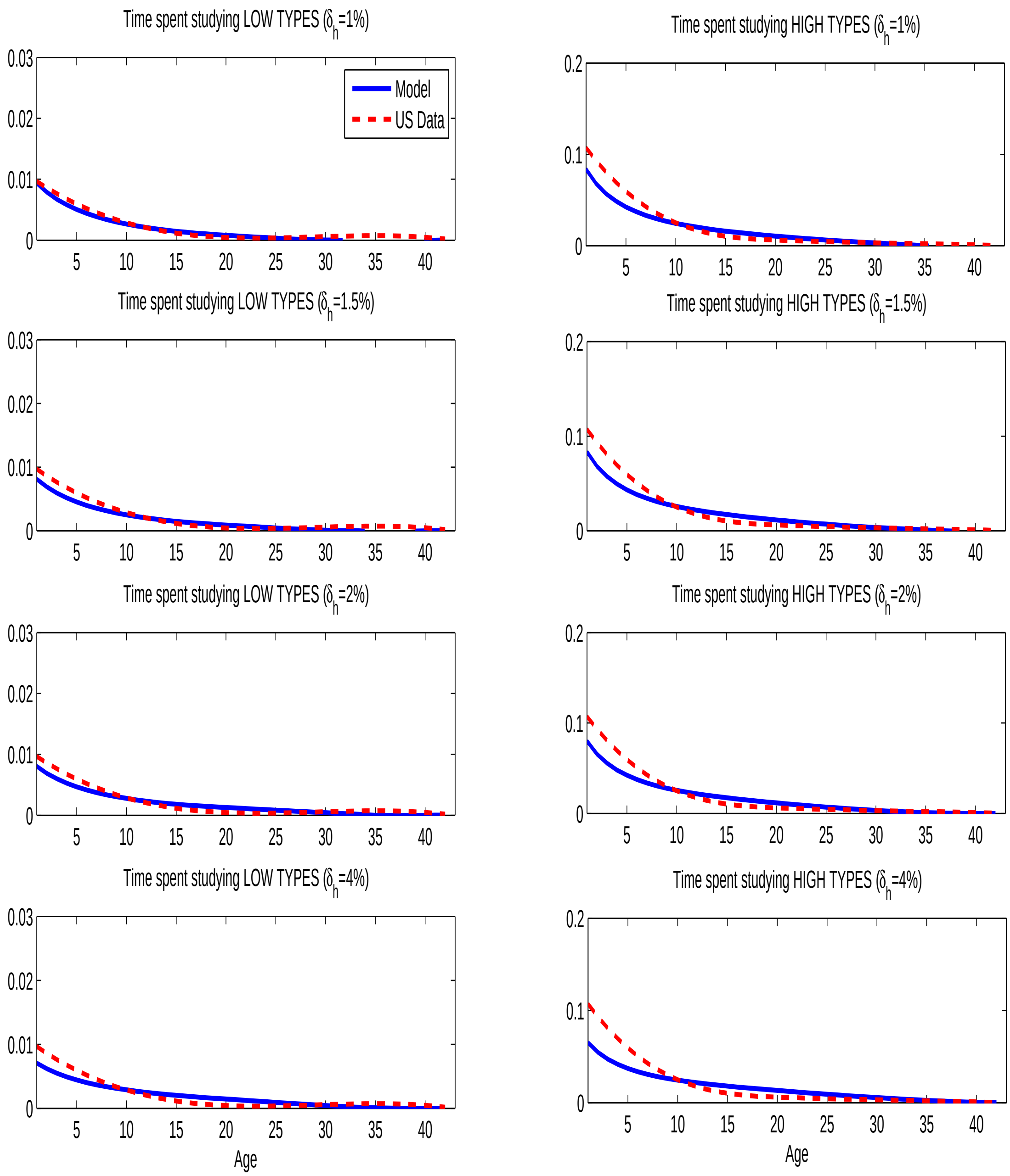


Figure 1.2: Estimated efficiency weights and productivity sequences

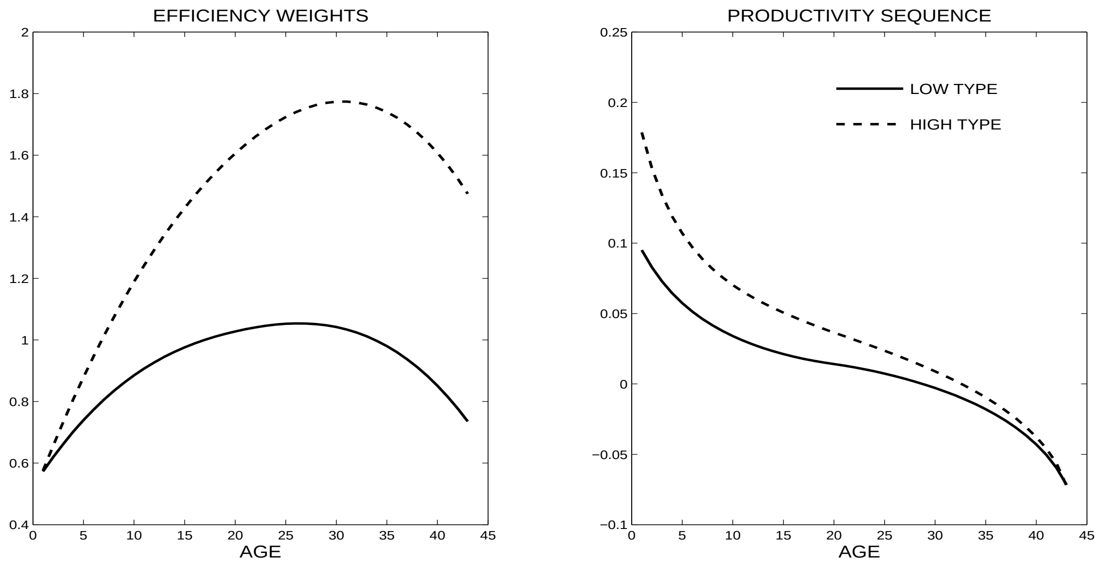


Figure 1.3: Steady-state values by age and type

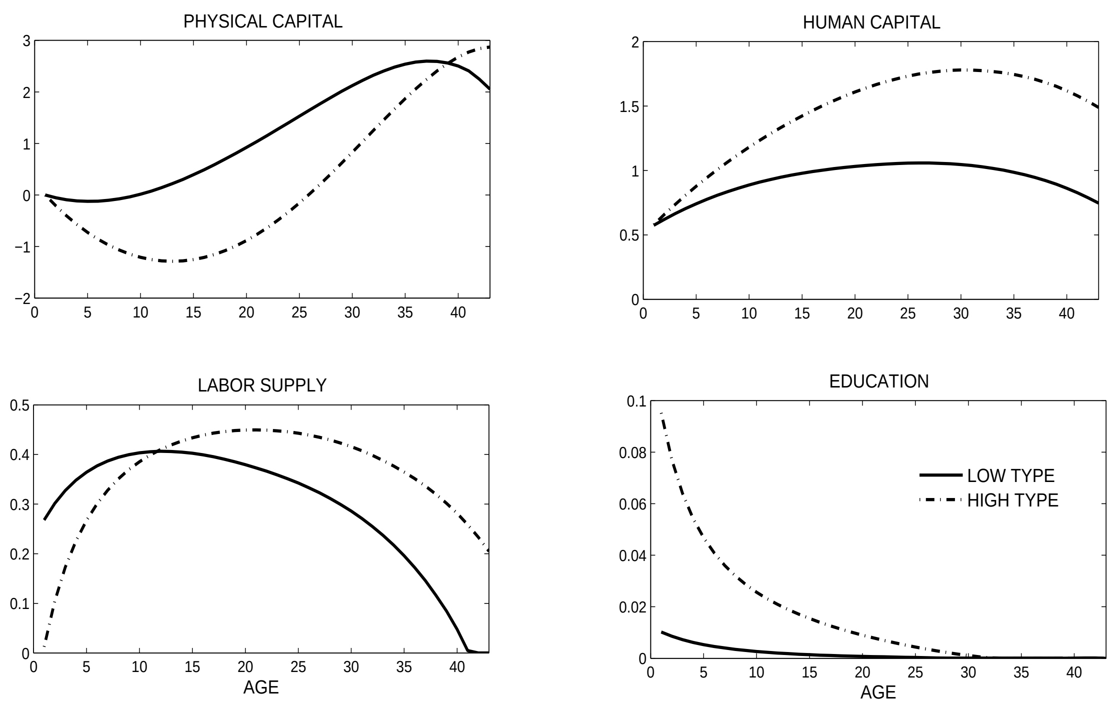


Figure 1.4: Life-cycle profiles

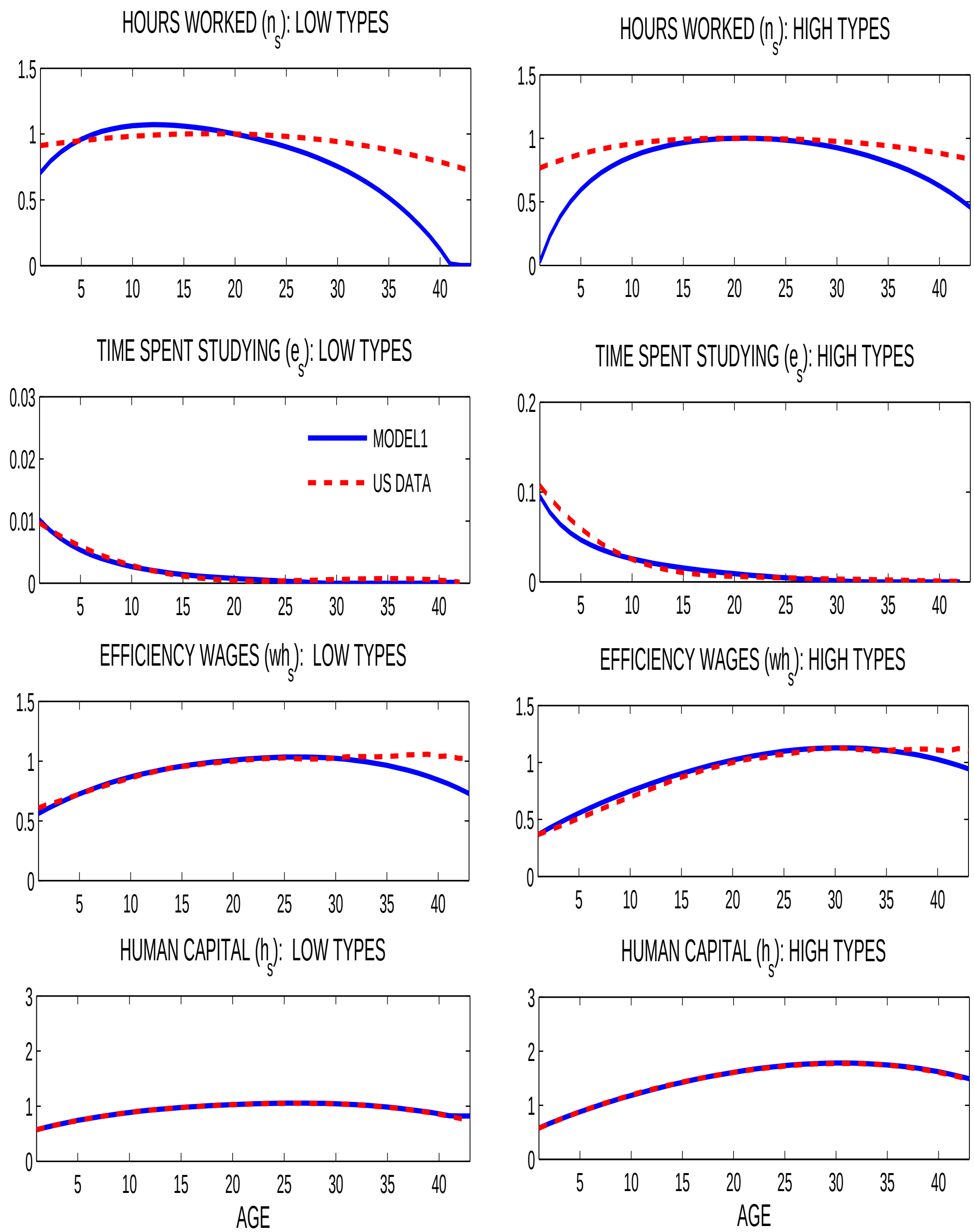


Figure 1.5: Impulse response functions for the aggregate economy

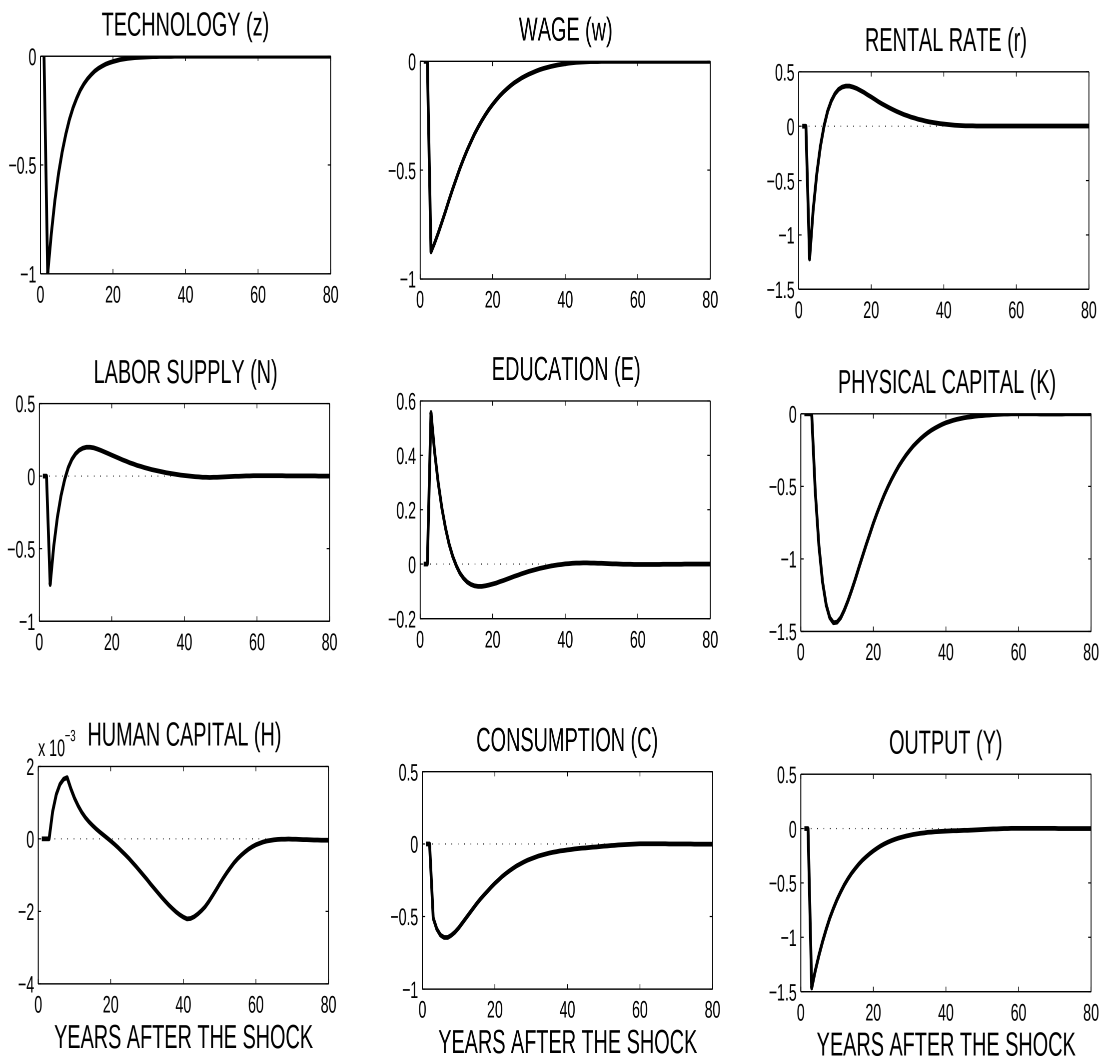


Figure 1.6: Impulse response functions of education by ability type and age group

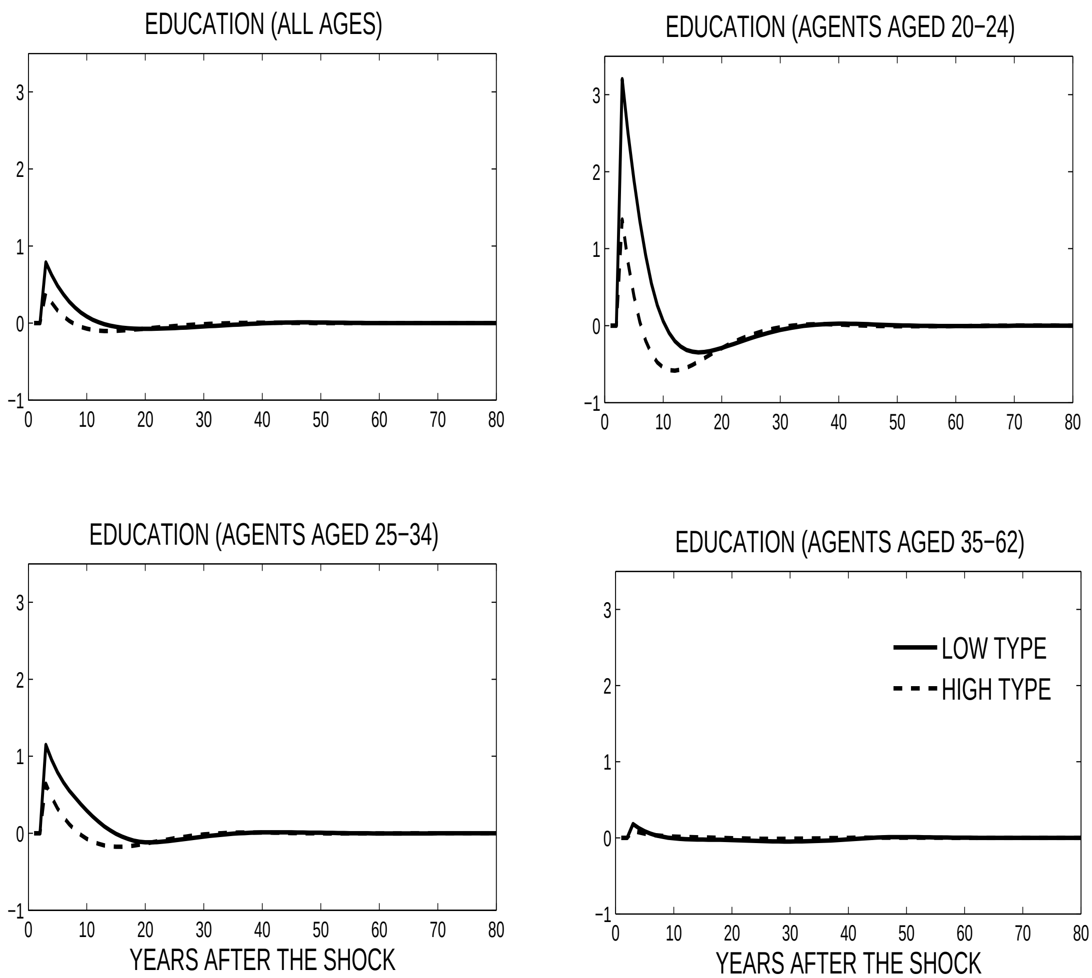


Figure 1.7: Impulse response functions of labor supply by ability type and age group

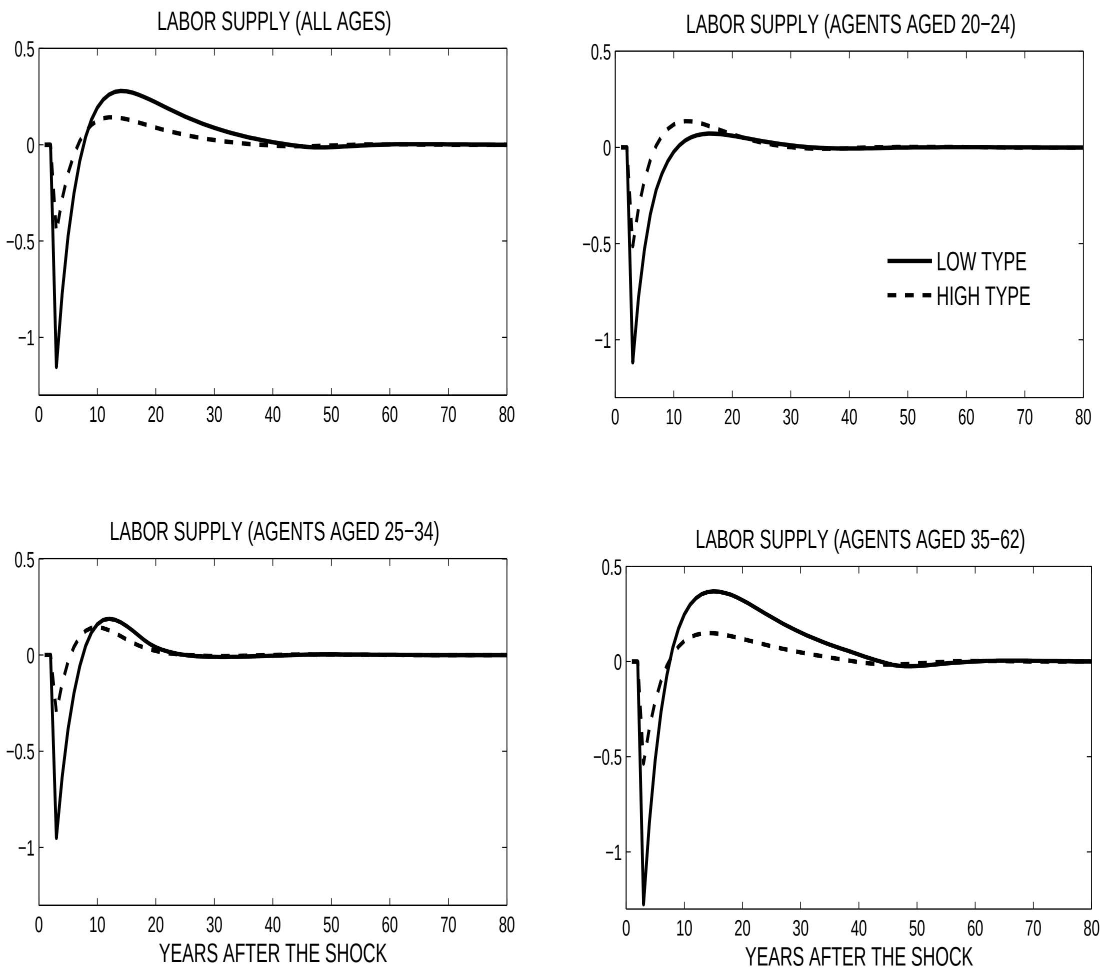


Figure 1.8: Impulse response functions with a common ϕ value

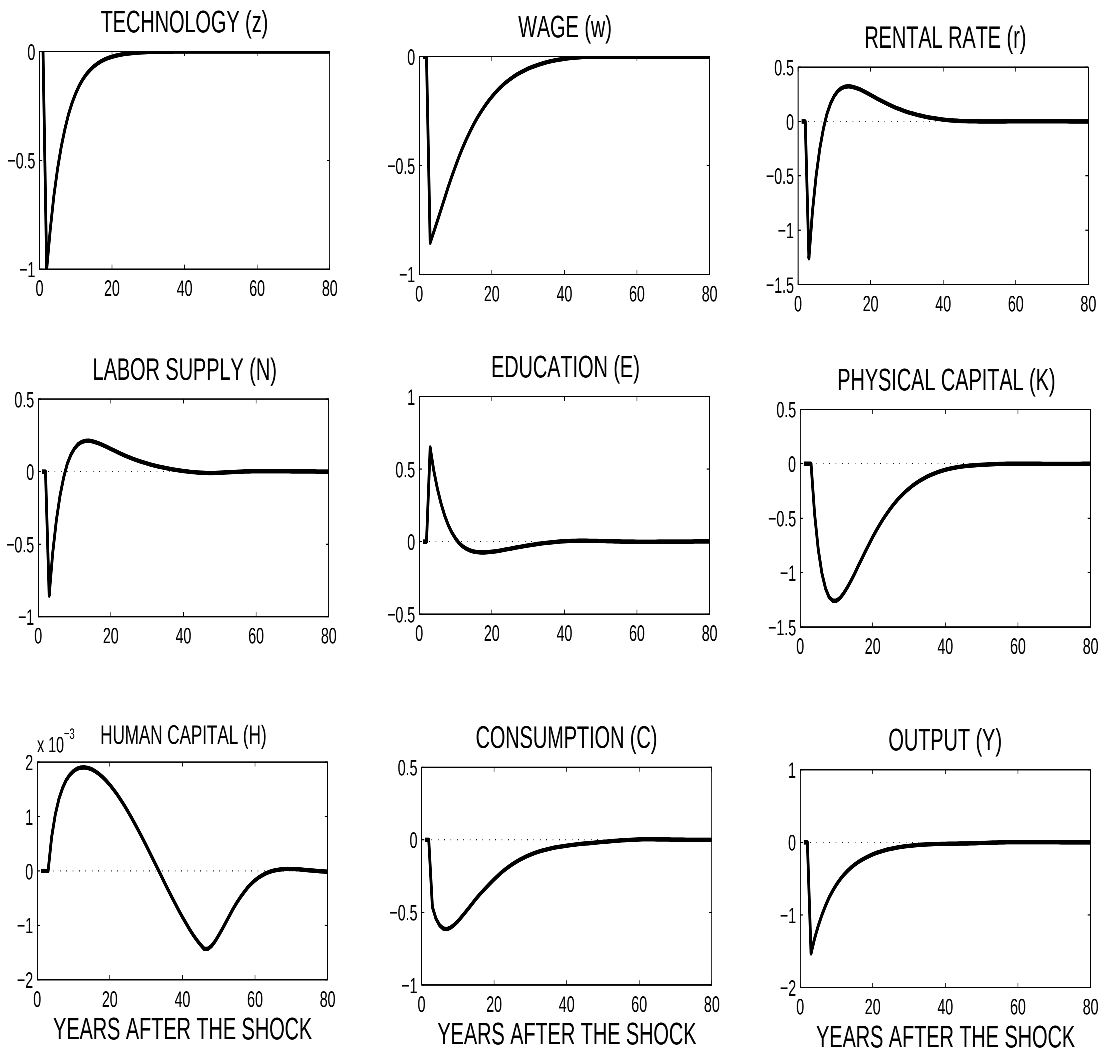


Figure 1.9: Impulse response functions of education with a common ϕ value

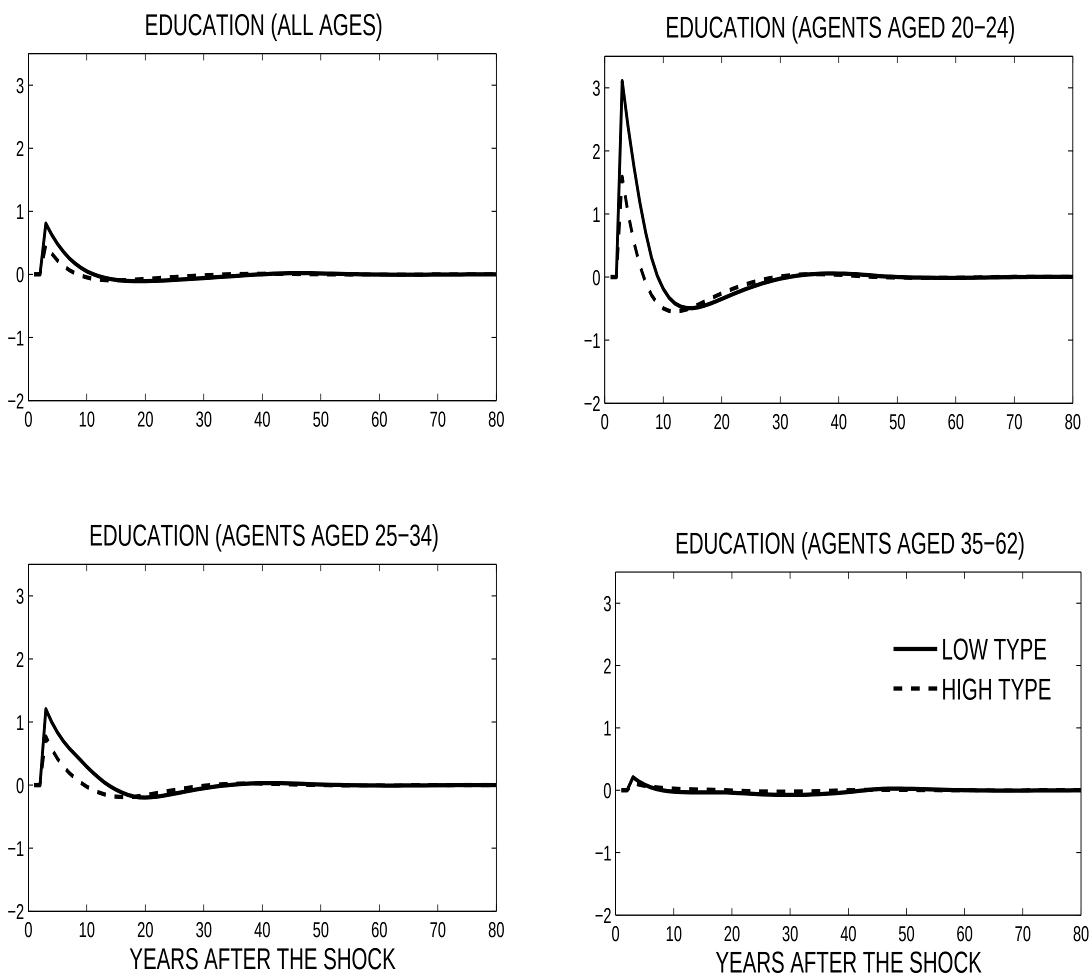


Figure 1.10: Life-cycle profiles with a common ϕ value

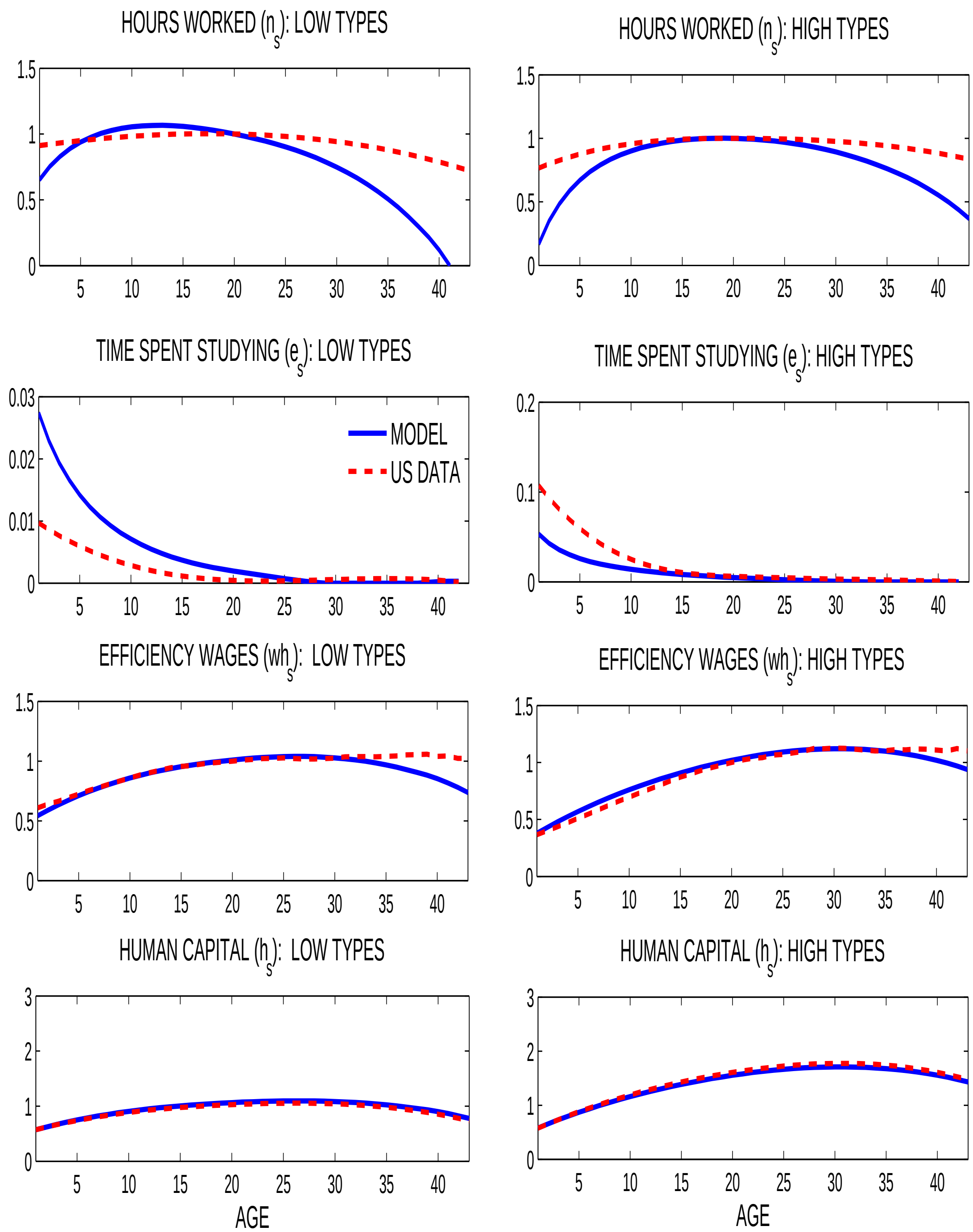


Figure 1.11: The impact of education costs on education

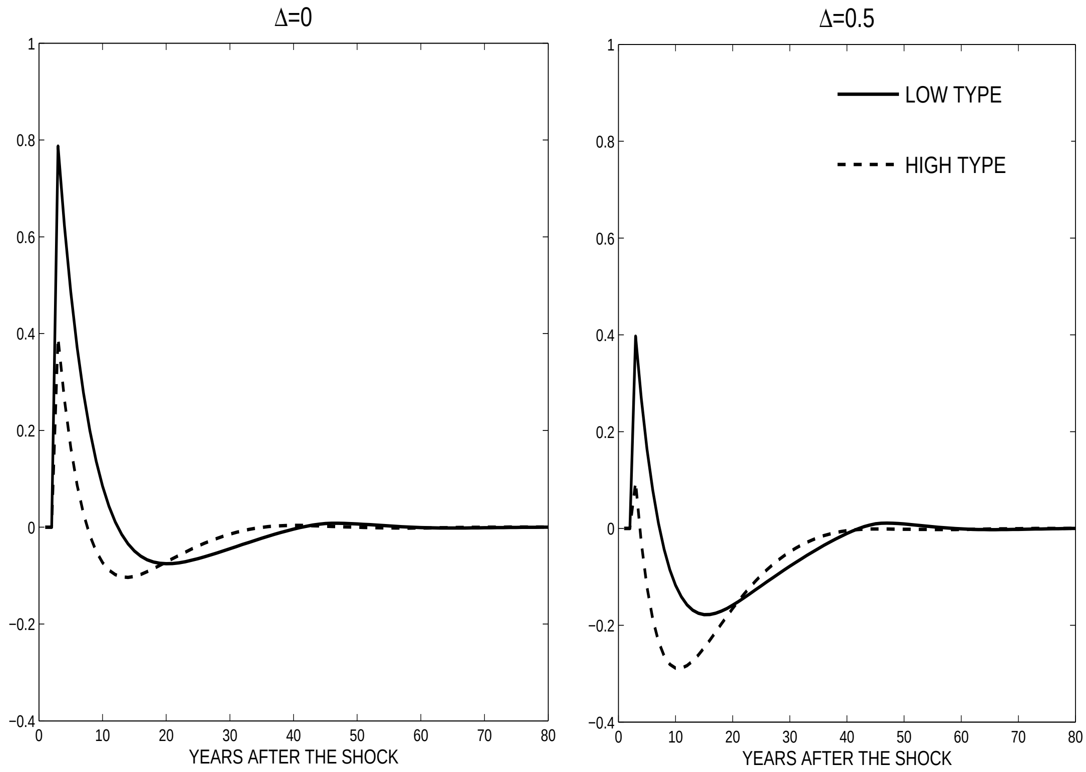


Figure 1.12: Deviation from HP trend of GDP and college enrollment rates

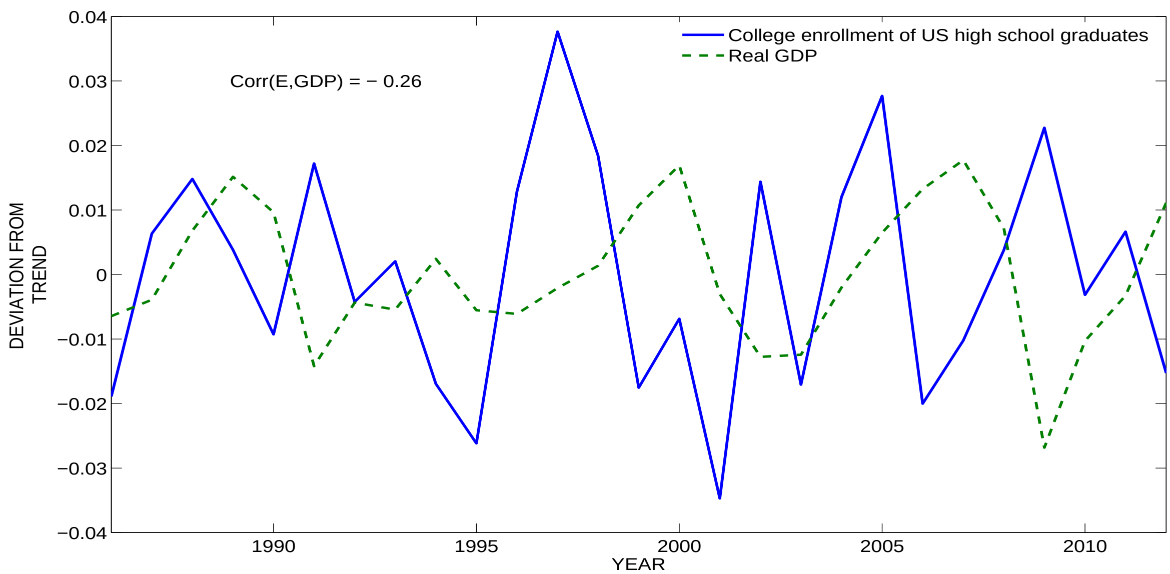
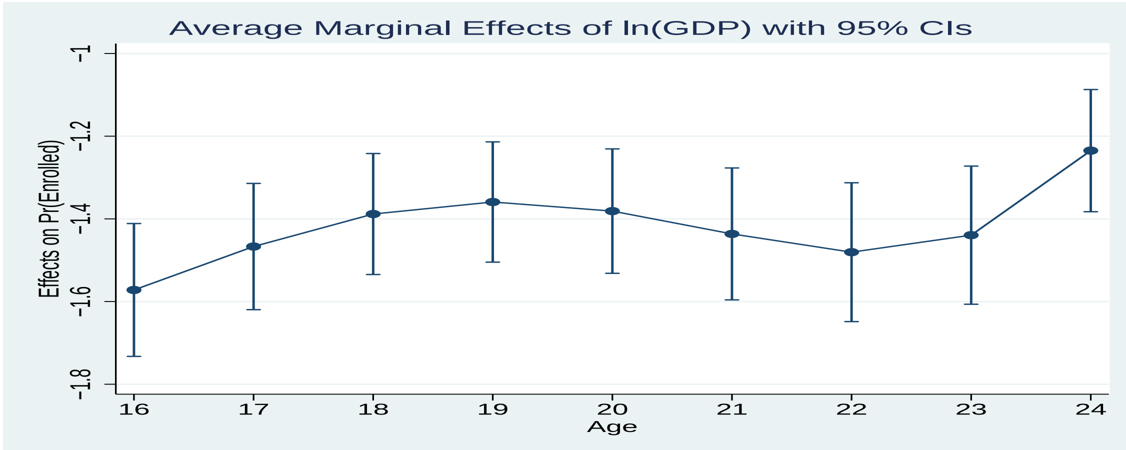
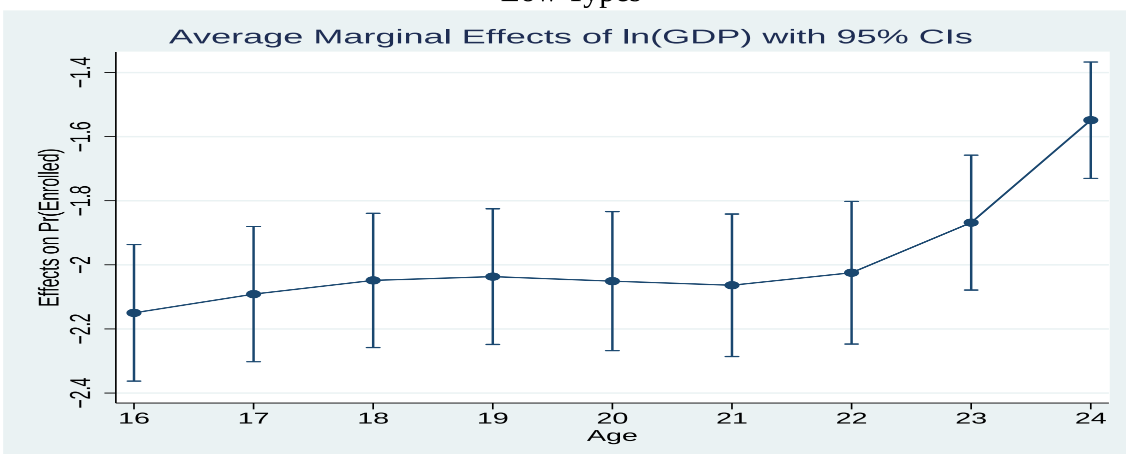


Figure 1.13: Average marginal effect of GDP by age

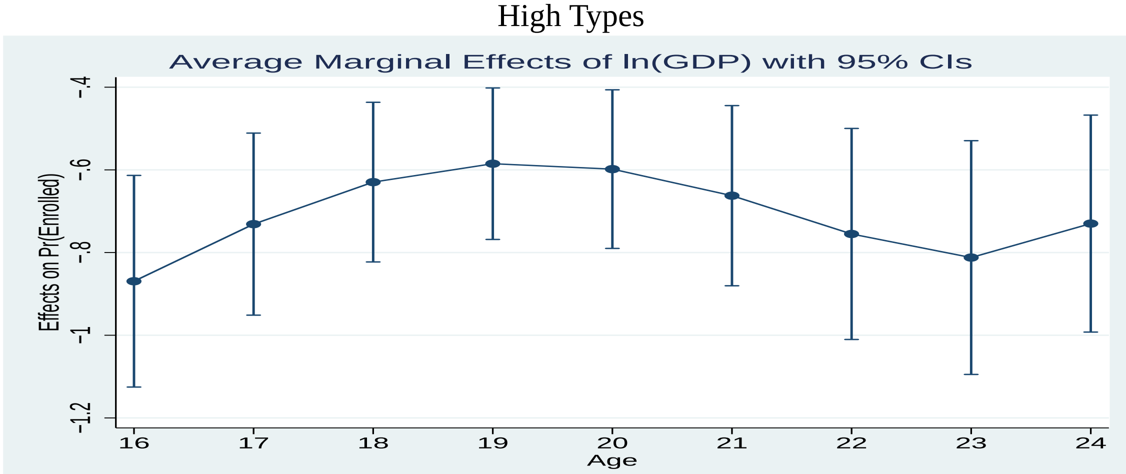
Aggregate Economy



Low Types



High Types



Appendix

Household's maximization problem:

$$max \qquad E_t \sum_{s=1}^{S_{max}} \beta^{s-1} \psi_s \left[\frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma} \right)^{1-\eta}}{1-\eta} \right]$$

by choosing $\{c_{s,t,i}\}_{s=1}^{S_{max}}$, $\{n_{s,t,i}\}_{s=1}^{S_r-1}$, $\{e_{s,t,i}\}_{s=1}^{S_r-2}$, $\{k_{s+1,t+1,i}\}_{s=1}^{S_{max}}$, $\{h_{s+1,t+1,i}\}_{s=1}^{S_r-1}$

subject to

$k_{s+1,t+1,i} = (1+r_t-\delta)k_{s,t,i} + (1-\tau_t)w_t n_{s,t,i} h_{s,t,i} - c_{s,t,i} - \Delta e_{s,t,i} + tr_t$, ($s = 1 : S_r - 1$)

$k_{s+1,t+1,i} = (1+r_t-\delta)k_{s,t,i} + b_t - c_{s,t,i} + tr_t$, ($s = S_r : S_{max}$)

$h_{s+1,t+1,i} = h_{s,t,i}\left(1-\delta_h\right) + \Omega_{s,i} h_{s,t,i} e_{s,t,i}^{\phi_i}$, ($s = 1 : S_r - 1$)

$e_{s,t,i} + n_{s,t,i} + m_{s,t,i} = 1$

$e_{s,t,i} \geq 0$, $n_{s,t,i} \geq 0$, $m_{s,t,i} \geq 0$

$m_{s,t,i} = 1$, $n_{s,t,i} = 0$ for $s = S_r : S_{max}$

The value function is given by:

$s = 1 : S_r - 1$

$$\begin{aligned} V(k_{s,t,i}, h_{s,t,i}) = {} & \frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma} \right)^{1-\eta}}{1-\eta} + \beta\psi_{s+1} E_t V(k_{s+1,t+1,i}, h_{s+1,t+1,i}) \\ & + \lambda_{s,t,i}[(1+r_t-\delta)k_{s,t,i} + (1-\tau_t)w_t n_{s,t,i} h_{s,t,i} - c_{s,t,i} - k_{s+1,t+1,i} \\ & - \Delta e_{s,t,i} + tr_t] + \mu_{s,t,i}\left[\Omega_{s,i} h_{s,t,i} e_{s,t,i}^{\phi} - h_{s+1,t+1,i} + h_{s,t,i}\left(1-\delta_h\right) \right] \end{aligned} \quad (1.7)$$

$s = S_r : S_{max}$

$$V(k_{s,t,i}) = \frac{(c_{s,t,i})^{1-\eta}}{1-\eta} + \beta\psi_{s+1}E_tV(k_{s+1,t+1,i})$$
$$+ \lambda_{s,t,i}\left[(1+r_t-\delta)k_{s,t,i} + b_t - c_{s,t,i} - k_{s+1,t+1,i} + tr_t\right] \quad (1.8)$$

First order conditions:

$s = 1 : S_r - 1$

$$w.r.t.\ c_{s,t,i}: \quad \lambda_{s,t,i} = c_{s,t,i}^{-\eta}m_{s,t,i}^{\gamma(1-\eta)} \quad (1.9)$$

$$w.r.t.\ n_{s,t,i}: \quad \lambda_{s,t,i} = \frac{\gamma c_{s,t,i}^{1-\eta}m_{s,t,i}^{\gamma(1-\eta)-1}}{(1-\tau_t)w_th_{s,t,i}} \quad (1.10)$$

$$w.r.t.\ k_{s+1,t+1,i}: \quad \lambda_{s,t,i} = \beta E_tV_k(k_{s,t,i},h_{s,t,i}) = \beta E_t\lambda_{s+1,t+1,i}(1+r_{t+1}-\delta) \quad (1.11)$$

$$w.r.t.\ e_{s,t,i}: \quad \gamma c_{s,t,i}^{1-\eta}m_{s,t,i}^{\gamma(1-\eta)-1} = \mu_{s,t,i}\phi_i\Omega_{s,i}h_{s,t,i}e_{s,t,i}^{\phi_i-1} - \Delta\lambda_{s,t,i} \quad (1.12)$$

$$w.r.t.\ h_{s+1,t+1,i}: \quad \mu_{s,t,i} = \beta E_tV_h(k_{s,t,i},h_{s,t,i}) = \beta E_t\left[\lambda_{s+1,t+1,i}(1-\tau_{t+1})w_{t+1}n_{s+1,t+1,i}\right]$$
$$+ \beta E_t\mu_{s+1,t+1,i}\left[\Omega_{s+1,i}e_{s+1,t+1,i}^{\phi_i} + (1-\delta_h)\right] \quad (1.13)$$

$s = S_r : S_{max}$

$$w.r.t.\ c_{s,t,i}: \quad \lambda_{s,t,i} = c_{s,t,i}^{-\eta} \quad (1.14)$$

$$w.r.t.\ k_{s+1,t+1,i}: \quad \lambda_{s,t,i} = \beta E_t\lambda_{s+1,t+1,i}(1+r_{t+1}-\delta) \quad (1.15)$$

Firm's maximization problem:

$$\underset{K_t, L_t}{max} \qquad \Pi_t = z_t K_t^{\alpha} L_t^{1-\alpha} - wL_t - rK_t$$

First order conditions:

$$w_t = (1-\alpha) z_t K_t^{\alpha} L_t{}^{-\alpha} \tag{1.16}$$

$$r_t = \alpha z_t K_t^{\alpha-1} L_t^{1-\alpha} \tag{1.17}$$

Chapter 2

Labor supply volatility in life-cycle RBC models

2.1 Introduction

This chapter investigates labor supply volatility in the context of RBC models with finitely-lived agents (i.e. life-cycle RBC models). One of the main shortcomings of RBC models is the inability to match the data regarding labor supply volatility. Specifically, the volatility is lower than empirical estimates. This problem is known as the volatility puzzle in RBC models. Several hypotheses have been considered in the literature in the context of standard RBC models[1]. These models could underestimate labor supply volatility because they ignore important features such as unemployment (Hansen, 1985), labor market search

[1] A standard RBC model is characterized by a representative agent who lives forever.

(Andolfatto, 1996), alternatives to market production (e.g. education and home production. See, for example, DeJong and Ingram, 2001; Einarsson and Marquis, 1998; Benhabib et al., 1991; Perli, 1998), and/or heterogeneity among agents (Maliar and Maliar, 2001; Gomme et al., 2004; Hansen and İmrohoroğlu, 2009). This chapter focuses on two hypotheses, education and agents' heterogeneity, within the context of life-cycle RBC models.

Previous literature (e.g. DeJong and Ingram, 2001 and Einarsson and Marquis, 1998) showed that labor supply volatility predicted by an RBC model matches the data when schooling is introduced into a representative-agent setting. Since education is counter-cyclical[2], individuals substitute schooling for work during economic downturns. Thus, the education sector provides an alternative to work and increases the volatility of labor supply. I show that this result no longer holds once heterogeneity is introduced in the model and agents face a finite lifetime. In this case, the benefits of education differ among agents and decline with aging. As a result, education is counter-cyclical only for certain types of individuals (e.g. young people). Other categories of agents do not consider the education sector as an alternative to work. Therefore, once we relax the representative agent assumption and consider a finite horizon, aggregate labor supply volatility is not particularly sensitive to the presence of schooling in the model.

On the contrary, heterogeneity plays an important role. Recent papers (e.g. Hansen and İmrohoroğlu, 2009; Gomme et al., 2004) suggested that RBC models may underestimate the volatility only for certain groups of individuals. In the data, for example, labor

[2]That is, more students enroll in school when the GDP level of the economy is below trend.

supply is more volatile for young compared to middle-age individuals. This fact cannot be captured by the baseline RBC model because of the representative-agent assumption. Therefore, introducing heterogeneity in the model may help to explain the volatility puzzle. By comparing different versions of a life-cycle RBC model, this chapter shows for the first time that heterogeneity in productivity is particularly important to improve the model's predictions regarding labor supply volatility.

Specifically, I build on the work in Chapter 1. I embed a Ben-Porath (1967) model of human capital accumulation into a life-cycle RBC setting. I incorporate two types of heterogeneity: age and productivity in learning. Thus, individuals differ both within and between ages. With respect to the first chapter, I include subsidies to education to further investigate the role of schooling in the model. The purpose is to determine which factors improve the model's predictions regarding labor supply volatility.

Results show that introducing heterogeneity in productivity increases the volatility of aggregate labor supply and changes the profile for hours volatility to better match the data. Since hours worked fluctuate more for low-productivity individuals compared to the rest of the population, heterogeneity in productivity can improve the ability of the model to predict labor supply volatility. This result is consistent with Maliar and Maliar (2001), who showed that hours worked become more volatile by incorporating heterogeneity in physical capital and skills[3] into an otherwise standard RBC model with infinitely lived agents. However, they do not differentiate the impact of the two types of heterogeneity: physical capital and

[3]Skills refer to efficiency at work, which is set exogenously. In my model, instead, efficiency at work is determined by the human capital stock accumulated by the individual through education. In this case, skills are determined endogenously.

skills. Therefore, it is not possible to understand which type is important for labor supply volatility. Further, contrary to their results, my model is able to replicate the empirical fact that hours worked are increasing in skills even for low values of the intertemporal elasticity of substitution for consumption. Since skill differences are endogenous in my model, I am also able to provide an explanation for why we observe this type of heterogeneity. Specifically, high-skilled agents are those individuals who are more effective learners and, therefore, spend more time studying. Finally, by introducing schooling in the model, I can quantify the impact of education on labor supply volatility.

The rest of the chapter is organized as follows. The model is presented in Section 2.2. The theoretical results and the implications about labor supply volatility are presented in Section 2.3. Section 2.4 concludes by summarizing the factors that affect labor supply volatility in life-cycle RBC models.

2.2 The Model

I build on the model developed in Chapter 1 and introduce subsidies to education. Specifically, I embed a Ben-Porath (1967) model of human capital accumulation into an RBC setting and include agents' heterogeneity by age and productivity in learning. In every period a new generation of equal size is born. Agents face an uncertain lifespan and can live a maximum of S_{max} periods. Conditional on survival, they must retire at age S_r. Individuals are born with a positive human capital endowment and a fixed ability level:

high or low. In any period, agents allocate their available time among work, school and leisure, and invest in capital (i.e. physical and human capital) in order to maximize their expected discounted lifetime utility:

$$\sum_{s=1}^{S_{max}} \left(\prod_{j=0}^{s-1} \varphi_j \right) \beta^{s-1} \left[\frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma} \right)^{1-\eta}}{1-\eta} \right], \tag{2.1}$$

subject to the budget constraints:

$$\begin{aligned}
&\text{for s} = 1, ..S_r - 1 : \\
&\quad k_{t+1,s+1,i} = (1 + r_t - \delta) k_{t,s,i} + (1 - \tau_t) w_t n_{t,s,i} h_{t,s,i} + sub * f(z_t, e_{t,s,i}) - c_{t,s,i} \\
&\qquad\qquad + tr_t - T_t \\
&\text{for s} = S_r, ..S_{max} - 1 : \\
&\quad k_{t+1,s+1,i} = (1 + r_t - \delta) k_{t,s,i} + b_t - c_{t,s,i} + tr_t - T_t \\
&\text{for s} = S_{max} : \\
&\quad c_{t,s,i} = (1 + r_t - \delta) k_{t,s,i} + b_t + tr_t - T_t
\end{aligned} \tag{2.2}$$

where t and s denote the time period and age, respectively. i denotes the ability type: $i = \{H, L\}$. φ refers to the survival probability, γ determines the disutility of working and studying, β is the discount factor and η determines the relative risk aversion. c is consumption, k is physical capital, h is human capital, n is labor supply, m is leisure, e is time spent in education, r is the rental rate of physical capital, δ is the depreciation rate of physical capital, w is the wage rate, τ is the labor income tax rate, b is the annual public pension benefit level, T is a lump-sum tax and tr is the government transfer of assets from deceased agents to surviving agents.

Human capital accumulates over time according to:

$$h_{t+1,s+1,i} = (1 - \delta_h)h_{t,s,i} + \Omega_{s,i}h_{t,s,i}e_{t,s,i}^{\phi_i}, \tag{2.3}$$

The parameter ϕ_i determines how many units of education contribute to human capital accumulation, δ_h is the depreciation rate of human capital and $\Omega_{s,i}$ determines the productivity in learning. I assume that $\Omega_{s,i}$ depends on two factors: age s and ability type i. First, the productivity in learning is negatively affected by age because learning abilities decrease over the life-cycle. Second, ability has a positive impact on the productivity in learning. High types are more productive in learning compared to low types of the same age. It is worth mentioning that Ω_s also determines the productivity at work. Individuals with a higher Ω_s are able to accumulate human capital faster. Therefore, they will acquire more skills and knowledge over their life-cycle. This, in turn, increases their productivity at work. Therefore, individuals with a higher productivity in learning are also more productive in the workplace.

The expression $sub * f(z_t, e_{t,s,i})$ is the amount of subsidy paid by the government and received by each student. The financial support is intended to cover living costs for students. It depends on the time spent studying, $e_{t,s,i}$, and the state of the economy, z_t. In particular, $f(z_t, e_{t,s,i}) = z_t^a e_{t,s,i}$. The parameter a determines the cyclicality of the subsidy.

This factor increases or decreases the amount of financial support depending on the performance of the economy. If $a > 0$, on average, the financial support is higher during a boom period. If $a < 0$, on average, the financial support is higher during a recession. The parameter sub, instead, determines the size of the financial support.

Subsidies are financed by lump-sum taxes, T:

$$sub * z_t^a E_t = T_t \sum_{s=1}^{Smax} \theta_s, \tag{2.4}$$

where E_t is the aggregate time spent studying at time t. Pension benefits are financed by labor income taxes, τ:

$$\tau_t w_t L_t = b_t \sum_{s=S_r}^{Smax} \theta_s. \tag{2.5}$$

Since the government cannot collect debt in this model, public expenditure must be entirely financed by tax revenue. Finally, the output in the economy is produced using a Cobb-Douglas technology:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{2.6}$$

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 $\varepsilon_t \sim N(0, \sigma^2)$. Given constant returns to scale and competitive markets, total output is produced by a single representative firm.

The calibration follows the procedure described in Section 1.2.2 of Chapter 1. Table 2.1 reports the calibrated parameters. Regarding the parameters sub and a, they are both set to zero in the first part of the chapter. Section 2.3.2 shows how the results are affected when the subsidy is introduced in the model.

2.2.1 Competitive equilibrium

Given the government policy (b_t, sub, T_t and τ_t), 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:

1. The individual policy rules solve the household's maximization problem.

2. Prices $\{w_t, r_t\}$ solve the representative firm's maximization problem.

3. The government balanced-budget constraint is satisfied.

4. The market-clearing condition is satisfied:

$$z_t K_t^{\alpha} L_t^{1-\alpha} = C_t + K_{t+1} - (1-\delta)K_t + \Delta E_t. \tag{2.7}$$

5. Individual decisions are consistent with aggregate outcomes:

$$L_t = \sum_{s=1}^{S_r - 1} \left(n_{s,t,H} h_{s,t,H} \xi + n_{s,t,L} h_{s,t,L} (1-\xi) \right) \theta_s, \tag{2.8}$$

$$K_t = \sum_{s=1}^{S_{max}} \left(k_{s,t,H}\xi + k_{s,t,L}(1-\xi)\right)\theta_s. \tag{2.9}$$

$$E_t = \sum_{s=1}^{S_r-1} \left(e_{s,t,H}\xi + e_{s,t,L}(1-\xi)\right)\theta_s. \tag{2.10}$$

2.2.2 Solution method

The non-stochastic steady state (i.e. $z^* = 1$) in the Overlapping Generations model has been computed using a guess and verify method. The algorithm can be summarized as follows. First, I guess the steady-state values of aggregate physical capital and labor supply in efficiency units. Then, I compute the wage rate, the rental rate of physical capital, the labor tax rate and the lump-sum tax. The factor prices are given by the first-order conditions of the firm's maximization problem. The labor income tax is determined by the replacement ratio of pension benefits. The lump-sum tax is derived from equation 2.4[4]. I then solve the household maximization problem for the two ability types by using backward induction and compute the aggregate values for labor in efficiency units and physical capital. Finally, the initial guesses are updated using the computed aggregate values and the procedure is repeated until convergence. The transitional dynamics are computed by log-linearizing the

[4]The aggregate value of education is given by the calibration. In fact, the model is calibrated to match the average time spent studying over the life cycle in US, E_t. Therefore, for a given sub value, I can directly compute the lump-sum tax, T.

first order conditions around the non-stochastic steady state.

2.3 Labor supply volatility

Table 2.2 shows the average business cycle statistics computed from 500 simulations[5] of several versions of the life-cycle RBC model, along with annual business cycle statistics from US data. Data for output, consumption and investment are from the US Bureau of Economic Analysis (1962-2012). Output is measured by real GDP, consumption by personal consumption expenditures and investment by gross private domestic investment. The data on labor supply are from the Current Population Survey, March Supplement (1962-2012). Hours worked are obtained using the answer to the question "How many hours did you actually work last week?". Both the actual and the simulated series are transformed by taking natural logarithms and detrended using the Hodrick-Prescott filter. The smoothing parameter is set to 6.25 (Ravn and Uhlig, 2002).

To better understand how human capital accumulation and heterogeneity in learning ability affect business cycle properties, and in particular time allocation, the version of the model outlined in Section 2.2 is compared to several simplified versions of the life-cycle RBC model. Model1 is the model presented in Section 2.2. This is the main specification in which agents are heterogeneous in age and productivity in learning. In the second version of the model, Model2, agents are heterogeneous in age only. Thus, individuals of a given age are equally productive in learning. This is the specification that most resembles

[5] Each simulation consists of 100 periods.

the model by Hansen and İmrohoroğlu (2009). However, while they look at learning by doing and on-the-job training, the focus of this chapter is on formal education. Model3 refers to a version of the life-cycle RBC model without human capital accumulation, and includes heterogeneity by age only. The Appendix shows the household's maximization problem for this model. The firm's maximization problem is the same as in Model1. In summary, Model1 includes both heterogeneity by age and productivity in learning. Model2 and Model3, instead, include only heterogeneity by age with and without human capital accumulation, respectively.

All parameters in the alternative specifications have been re-calibrated following the procedure described in Section 1.2.2 of Chapter 1, except for the relative risk aversion parameter η. This parameter is set to match US output volatility in Model1. Since the purpose of this section is to analyze how different versions of the model are able to match business cycle facts, the comparison is possible only by considering the same value of relative risk aversion[6]. Table 2.3 reports the calibrated values for alternative versions of the model. Figure 2.1 shows the comparison between the life-cycle profiles generated by Model1 and the empirical profiles estimated from US data[7]. Figure 2.2 shows the calibrated productivity in learning profile together with life-cycle profiles for Model2, which has one ability type.

As shown by Table 2.2, the volatility of hours worked is underestimated by all models.

[6] I also experimented with calibrating the parameter to match US output volatility in each version of the model. However, the predictions of the models are qualitatively the same.

[7] Similarly to Chapter 1, data on earnings and hours worked are from PSID (1068-2008). Data on time spent studying are from ATUS (2003-2011). For details on the estimation of these profiles see Section 3 in Chapter 1.

However, the model with heterogeneity by productivity in learning can explain a higher percentage of the volatility empirically estimated. Model2 can explain 42% of the volatility observed in the data. The percentage increases to 60% when productivity differences among agents are introduced. The performance in terms of labor supply volatility of the model with one ability type is very similar to the performance of the model by Hansen and İmrohoroğlu (2009). In fact, their model includes heterogeneity by age only and it is able to explain at most 37% of the empirical volatility. Instead, Gomme et al. (2004) were able to explain a higher percentage, 59%, by introducing home production into a life-cycle RBC model. With respect to their paper, this chapter shows that heterogeneity in productivity is of similar importance in improving the model's predictions in terms of labor supply volatility.

Introducing heterogeneity in productivity generates differences among agents in terms of the cost of reducing hours worked. Reducing hours worked is cheaper for agents with a lower human capital stock because they give up a lower labor income. Therefore, when the shock hits the economy, these agents reduce hours worked more and their volatility increases. In fact, Model1 is consistent with US data in predicting a higher volatility for low types compared to high types. This is also empirically documented in Ríos-Rull (1993). Since low types have accumulated a lower human capital stock in the steady state, it is less expensive for them to reduce hours worked and give up labor income. Therefore, their labor supply volatility is higher compared to that of high-ability agents. With one ability type (i.e. Model2), instead, the productivity profile is more similar to the profile of high types (see

Figure 2.2). Thus, the volatility of labor supply is closer to that of high types from Model1. As a consequence, the model produces a lower labor supply volatility. This result suggests that, in order to increase the ability of the model to match labor supply volatility in the data, heterogeneity by age is not enough. It is important to include heterogeneity by productivity as well. The presence of low types increases the volatility of hours worked.

Finally, human capital differences among agents in the model (due to both age and productivity) also have implications regarding the volatility profile. Figure 2.4 shows the volatility of hours worked (relative to output volatility) by age group. The model is able to explain the volatility of older agents. However, it fails to explain the volatility of young agents. Further, in the data and in Model1, the profile is U-shaped: labor supply is more volatile for young and old agents compared to middle-age agents. Instead, the life-cycle RBC model without human capital, Model3, predicts an increasing volatility profile, which is not consistent with the data. Gomme et al. (2004) showed that, in a life-cycle RBC model with mandatory retirement, agents who are closer to retirement perceive the shock to be more transitory. Thus, the intertemporal substitution is higher and labor supply is more volatile for older agents. The current chapter shows that the introduction of human capital increases the volatility for young agents who are more willing to reduce hours worked because they earn a lower labor income, are more productive in learning and benefit more from education. This causes the volatility profile to assume a "U" shape. Also Hansen and İmrohoroğlu (2009) find similar results: the volatility profile is increasing when human capital is constant across agents, while it assumes a "U" shape when human capital differences among agents are introduced in the model.

2.3.1 The education sector

Based on the results discussed in the previous section, Model1 outperforms the alternative specifications. Is this due to the presence of the education sector or to differences among agents in terms of human capital? Can schooling increase volatility? Since schooling provides an alternative to work, having the education sector in the model could increase labor supply volatility. This is certainly true in an RBC model with identical agents. With heterogeneity, instead, the benefits from education differ among agents. As a result, labor supply volatility may or may not increase at the aggregate level. In order to answer this question, an alternative model has been considered, Model4, where human capital is exogenously determined. In this case, agents are heterogeneous by age and productivity at work. However, there is no education sector. Therefore, differences in productivity at work (i.e. differences in the human capital stock) are exogenously given and determined by the calibrated human capital life-cycle profile from Model1 (see the two graphs at the bottom of Figure 2.1). The calibrated parameters are reported in Table 2.3, while the life-cycle profiles for this model are in Figure 2.5.

Table 2.4 shows the business cycle statistics for the full model with schooling, Model1, and the simplified version with exogenous human capital, Model4. As shown by the table, labor supply volatility is not significantly affected by the presence of schooling in the model. When education is present in the model, low types are likely to substitute schooling for work. Thus, their volatility increases. Instead, labor supply volatility of high types is lower when education is introduced in the model. There are two explanations for this result. First, high types are not likely to substitute work with schooling because their opportunity cost of education is high and the marginal benefit is low. Second, they have a stronger incentive to substitute leisure for work when education is absent from the model. In this case, young high-types borrow less capital because they do not need to finance education. As a result, their savings are higher later in life. When the shock hits the economy, they reduce hours worked more to increase leisure time. Leisure becomes a better alternative to work when education is absent. Therefore, on one hand, labor supply volatility increases for low types when schooling is introduced in the model. On the other hand, the volatility decreases for high types. The two effects offset each other and aggregate labor supply volatility relative to output volatility is very similar in both models.

These results suggest that labor supply volatility is mainly affected by differences in the human capital stock, but whether the stock is set exogenously or determined endogenously does not have a significant impact. Having education in the model increases volatility for certain groups only. Overall the volatility may increase or decrease. In any case, the impact is low. Nevertheless, Model1 remains the preferred specification because it is able to explain why we observe differences in productivity at work among individuals. In this chapter, in particular, differences in productivity are determined by the human capital stock accumulated by agents through formal education.

2.3.2 Subsidies to education

This section investigates the impact of education subsidies on the model's predictions. I solve the model for several values of the parameters sub and a. For clarity of exposition, only a subset of the results is reported in the chapter: $sub = \{0, 0.2, 0.4\}$ and $a = \{-1, 0, 1\}$. For each value considered, the model's parameters are the same as in the baseline model. Figures 2.6 and 2.7 show the life-cycle profiles for the main variables of interest for different values of the parameter sub. Note that the non-stochastic steady state does not depend on the cyclicality of the subsidy (i.e. a). As shown by the figures, as the subsidy level increases, individuals spend more time studying early on in the life cycle. Since the subsidy increases the benefit to education and individuals are more productive in learning when young, it is optimal to increase the investment in human capital early in the life cycle. Further, they need to borrow less physical capital initially because they are able to cover living costs (i.e. c) with the subsidy.

Business cycle statistics are reported in Tables 2.5 through 2.7. Shaded columns refer to the statistics from the baseline model without subsidies. Figures 2.8 through 2.10 show the impulse responses of education after a negative shock is introduced in the model. Obviously, an increase in the subsidy increases the incentive to study. Therefore, education becomes more volatile and more counter-cyclical. Consequently, labor supply volatility increases. However, the impact on labor supply volatility is lower if agents receive a higher support during boom periods (i.e. $a = 1$).

If the subsidy is counter-cyclical and the financial support is high enough (i.e. $sub =$

0.42), the model is able to match labor supply volatility observed in the data (see Table 2.8). Only in this case, education is able to explain the volatility puzzle in a life-cycle RBC model. The reason is that a strong counter-cyclical subsidy promotes schooling during economic downturns for all agents in the economy, including high types and old individuals. As a result, the majority of the population has a strong incentive to substitute work with schooling, which increases aggregate labor supply volatility. This mechanism is successful when the subsidy level is very high (i.e. $sub = 0.42$). Such a high level may not be realistic. Moreover, in this case, the predictions of the model at the individual level are not consistent with the empirical evidence. For example, labor supply volatility of young and old agents is higher than that empirically estimated. Further, the model is no longer able to reproduce a nice U-shaped volatility profile. Therefore, education is not able to explain the volatility puzzle in the context of life-cycle RBC models under realistic assumptions.

2.4 Conclusions

This chapter investigates labor supply volatility in RBC models with finitely-lived heterogeneous agents. It contributes to the RBC literature by showing that it is possible to improve the ability of RBC models to predict labor supply volatility by modeling heterogeneity in productivity among agents.

Results show that hours worked fluctuate more for low-productivity individuals compared to the rest of the population, which is consistent with US data. Therefore, aggregate labor supply volatility increases when modeling productivity differences among agents. The presence of low types in the model is particularly important. Since they reduce hours worked more compared to high types, aggregate labor supply volatility is higher when this type of agent is included in the model. A model that does not include productivity differences among agents can explain 42% of the volatility in the data. The percentage increases to 60% when heterogeneity in productivity is introduced.

Further, previous literature showed that the volatility of hours worked increases by introducing schooling in a representative-agent setting. I show that this result no longer holds if agents are heterogeneous and face a finite lifetime. Aggregate labor supply volatility is shown not to be particularly sensitive to how the productivity differences among agents materialize in the model. The key feature in affecting the volatility profile is the wage profile. Although wages are determined in part by human capital levels, it does not matter if the human capital profile is set exogenously or determined endogenously through formal modeling of the education sector.

Finally, education can explain the volatility puzzle in this setting only under unrealistic assumptions. When the incentive to study is strong due to the presence of high and countercyclical education subsidies, the majority of individuals in the economy substitute work with schooling during recessions and benefit from educational assistance. In this case, the model is able to match the volatility of hours worked estimated from US data. However, the subsidy level required is unrealistically high. Further, the model's performance decreases relative to other statistics.

Tables and Figures

Table 2.1: Calibration of Model1 ($\delta_h = 0.5\%$)

Parameter	Calibrated value	Set to target	Value from US data	Value from the model
S_{max}	58	life expectancy at age 20	57.2	57.5
S_r	43	ratio of retired people to active population	21.6%	21.7%
γ	1.85	n^*	0.33	0.33
η	1.17	σ_Y	1.35	1.35
δ	0.06	average annual real interest rate	6%	6%
β	0.9434	average physical capital to output ratio	3	3
ϕ_H	0.106	e_H^*	0.017	0.017
ϕ_L	0.025	e_L^*	0.002	0.002

Table 2.2: Business cycle statistics

X	σ_X				$\frac{\sigma_X}{\sigma_Y}$				$corr(X,Y)$			
	Data	Model1	Model2	Model3	Data	Model1	Model2	Model3	Data	Model1	Model2	Model3
Y	1.35	1.35	1.25	1.21	1	1	1	1	1	1	1	1
C	1.12	0.45	0.47	0.47	0.83	0.33	0.38	0.39	0.91	0.96	0.96	0.96
I	6.72	10.5	8.93	7.97	4.8	7.78	7.14	6.59	0.92	0.97	0.98	0.98
N	1.26	0.76	0.49	0.50	0.93	0.56	0.39	0.41	0.86	0.97	0.96	0.98
N_L	1.49*	1.16	-	-	0.89	0.86	-	-	0.85*	0.99	-	-
N_H	0.64*	0.47	-	-	0.61	0.35	-	-	0.77*	0.95	-	-
N (20-24)	2.20	0.75	0.33	0.40	1.63	0.56	0.26	0.33	0.79	0.98	0.96	0.98
N (25-34)	1.47	0.54	0.26	0.42	1.09	0.40	0.19	0.35	0.83	0.99	0.94	0.98
N (35-44)	1.07	0.56	0.31	0.46	0.79	0.41	0.25	0.38	0.85	0.96	0.97	0.98
N (45-54)	1.06	0.96	0.52	0.58	0.78	0.71	0.40	0.47	0.85	0.84	0.99	0.98
N (55-62)	1.09	1.26	0.87	0.74	0.81	0.93	0.67	0.60	0.77	0.96	0.99	0.98
N_L*(20-24)*	2.61*	1.10	-	-	1.93	0.81	-	-	0.76*	0.99	-	-
N_L*(25-34)*	1.84*	0.96	-	-	1.36	0.71	-	-	0.83*	0.99	-	-
N_L*(35-44)*	1.49*	0.99	-	-	1.23	0.73	-	-	0.83*	0.99	-	-
N_L*(45-54)*	1.30*	1.17	-	-	0.96	0.87	-	-	0.87*	0.99	-	-
N_L*(55-62)*	1.23*	1.71	-	-	0.91	1.27	-	-	0.79*	0.99	-	-
N_H *(20-24)*	1.43*	0.53	-	-	1.06	0.39	-	-	0.55*	0.95	-	-
N_H*(25-34)*	0.80*	0.33	-	-	0.59	0.24	-	-	0.78*	0.92	-	-
N_H *(35-44)*	0.64*	0.32	-	-	0.47	0.24	-	-	0.66*	0.92	-	-
N_H*(45-54)*	0.72*	0.45	-	-	0.53	0.33	-	-	0.56*	0.96	-	-
N_H*(55-62)*	1.00*	0.86	-	-	0.74	0.64	-	-	0.37*	0.97	-	-

Y is output, C is consumption, I is investment, N is labor supply, N_L is labor supply for low types and N_H is labor supply for high types.* Refers to time period 1992-2012: hours worked for the two ability types can be estimated starting from 1992 only because the question about education achievement in CPS was changed in 1992. Thus, in order to have a definition of ability type consistent over time, N_L and N_H have been estimated using data from 1992 to 2012 only.

Table 2.3: Calibration of the alternative specifications

Specification	Parameter	Calibrated value	Set to target	Value from US data	Value from the model
Model2	γ	1.89	n^*	0.33	0.33
	ϕ	0.09	e^*	0.007	0.007
Model3	γ	1.9	n^*	0.33	0.33
Model4	γ	1.3	n^*	0.33	0.33

The remaining parameters are the same as in Table 2.1.

Table 2.4: The role of schooling

X	σ_X		$\frac{\sigma_x}{\sigma_Y}$		$corr(X,Y)$	
	Model 1	Model 4	Model 1	Model 4	Model 1	Model 4
Y	1.35	1.35	1	1	1	1
C	0.45	0.44	0.33	0.33	0.96	0.98
I	10.5	10.7	7.78	7.93	0.98	0.98
N	0.76	0.74	0.56	0.55	0.96	0.97
N_L	1.16	1.13	0.86	0.84	0.99	0.98
N_H	0.47	0.49	0.35	0.36	0.95	0.96
N(20-24)	0.75	0.74	0.56	0.55	0.98	0.98
N(25-34)	0.54	0.57	0.40	0.42	0.99	0.99
N(35-44)	0.56	0.58	0.41	0.43	0.96	0.95
N(45-54)	0.96	0.78	0.71	0.58	0.84	0.96
N(55-62)	1.26	1.22	0.93	0.90	0.96	0.98

Table 2.5: Business cycle statistics: Acyclical subsidy

SUB:	0	0.2	0.4	0	0.2	0.4	0	0.2	0.4
X	σ_X			$\frac{\sigma_X}{\sigma_Y}$			$corr(X,Y)$		
Y	1.35	1.47	1.50	1	1	1	1	1	1
C	0.45	0.43	0.42	0.33	0.30	0.28	0.96	0.98	0.95
I	10.5	8.35	8.69	7.78	5.69	5.79	0.98	0.98	0.98
N	0.76	0.86	1.04	0.56	0.59	0.69	0.97	0.99	0.99
N_L	1.16	1.31	1.37	0.86	0.89	0.91	0.99	0.99	0.99
N_H	0.47	0.64	0.85	0.35	0.44	0.57	0.95	0.97	0.98
E	0.54	0.98	2.18	0.29	0.67	1.45	-0.93	-0.99	-0.99
E_L	0.75	1.17	2.42	0.39	0.80	1.61	-0.84	-0.97	-0.99
E_H	0.39	0.84	1.96	0.24	0.57	1.31	-0.46	-0.97	-0.99
N (20-24)	0.75	0.98	2.00	0.56	0.67	1.33	0.98	0.99	0.99
N (25-34)	0.54	0.62	0.69	0.40	0.42	0.46	0.99	0.86	0.94
N (35-44)	0.56	0.81	0.89	0.41	0.55	0.59	0.96	0.76	0.75
N (45-54)	0.96	0.93	1.03	0.71	0.63	0.67	0.84	0.98	0.92
N (55-62)	1.26	1.48	1.54	0.93	1.01	1.03	0.96	0.98	0.95

Table 2.6: Business cycle statistics: Cyclical subsidy (a=1)

SUB:	0	0.2	0.4	0	0.2	0.4	0	0.2	0.4
X	σ_X			$\frac{\sigma_X}{\sigma_Y}$			$corr(X,Y)$		
Y	1.35	1.47	1.47	1	1	1	1	1	1
C	0.45	0.43	0.42	0.33	0.29	0.29	0.96	0.98	0.96
I	10.5	8.33	8.49	7.78	5.67	5.78	0.98	0.98	0.98
N	0.76	0.85	0.93	0.56	0.58	0.63	0.97	0.99	0.98
N_L	1.16	1.31	1.34	0.86	0.89	0.91	0.99	0.99	0.99
N_H	0.47	0.62	0.67	0.35	0.42	0.46	0.95	0.97	0.99
E	0.54	0.59	0.54	0.29	0.40	0.37	-0.93	-0.99	-0.99
E_L	0.75	0.75	0.66	0.39	0.51	0.45	-0.84	-0.95	-0.97
E_H	0.39	0.47	0.41	0.24	0.32	0.28	-0.46	-0.95	-0.97
N (20-24)	0.75	0.89	1.08	0.56	0.61	0.73	0.98	0.99	0.99
N (25-34)	0.54	0.61	0.66	0.40	0.42	0.45	0.99	0.85	0.93
N (35-44)	0.56	0.81	0.89	0.41	0.55	0.61	0.96	0.76	0.76
N (45-54)	0.96	0.93	1.05	0.71	0.63	0.71	0.84	0.98	0.92
N (55-62)	1.26	1.48	1.56	0.93	1.01	1.06	0.96	0.98	0.95

Table 2.7: Business cycle statistics: Cyclical subsidy (a=-1)

SUB:	0	0.2	0.4	0	0.2	0.4	0	0.2	0.4
X	σ_X			$\frac{\sigma_X}{\sigma_Y}$			$corr(X,Y)$		
Y	1.35	1.47	1.53	1	1	1	1	1	1
C	0.45	0.44	0.42	0.33	0.30	0.28	0.96	0.98	0.99
I	10.5	8.37	8.90	7.78	5.69	5.82	0.98	0.98	0.98
N	0.76	0.87	1.15	0.56	0.59	0.75	0.97	0.99	0.99
N_L	1.16	1.32	1.40	0.86	0.90	0.91	0.99	0.99	0.99
N_H	0.47	0.66	1.02	0.35	0.45	0.92	0.95	0.97	0.98
E	0.54	1.37	3.87	0.29	0.93	2.53	-0.93	-0.99	-0.99
E_L	0.75	1.58	4.24	0.39	1.08	2.77	-0.84	-0.97	-0.99
E_H	0.39	1.20	3.57	0.24	0.82	2.33	-0.46	-0.97	-0.99
N (20-24)	0.75	1.08	2.93	0.56	0.74	1.92	0.98	0.99	0.99
N (25-34)	0.54	0.63	0.73	0.40	0.43	0.48	0.99	0.86	0.94
N (35-44)	0.56	0.81	0.89	0.41	0.55	0.58	0.96	0.76	0.75
N (45-54)	0.96	0.92	1.02	0.71	0.63	0.67	0.84	0.98	0.92
N (55-62)	1.26	1.47	1.53	0.93	1.00	1.00	0.96	0.98	0.94

Table 2.8: Business cycle statistics when the model matches labor supply volatility

X	σ_X		$\frac{\sigma_X}{\sigma_Y}$		$corr(X,Y)$	
	Data	Model $sub = 0.42$ $a = -1$	Data	Model $sub = 0.42$ $a = -1$	Data	Model $sub = 0.42$ $a = -1$
Y	1.35	1.55	1	1	1	1
C	1.12	0.42	0.83	0.27	0.91	0.96
I	6.72	9.36	4.8	6.04	0.92	0.97
N	1.26	1.26	0.93	0.81	0.86	0.99
N_L	1.49	1.35	1.10	0.87	0.85	0.99
N_H	0.64	1.26	0.47	0.81	0.77	0.99
N (20-24)	2.20	3.96	1.63	2.56	0.79	0.99
N (25-34)	1.47	0.76	1.09	0.49	0.83	0.96
N (35-44)	1.07	1.05	0.79	0.68	0.85	0.60
N (45-54)	1.06	0.94	0.78	0.61	0.85	0.94
N (55-62)	1.09	1.46	0.81	0.94	0.77	0.96

Figure 2.1: Life-cycle profiles Model1

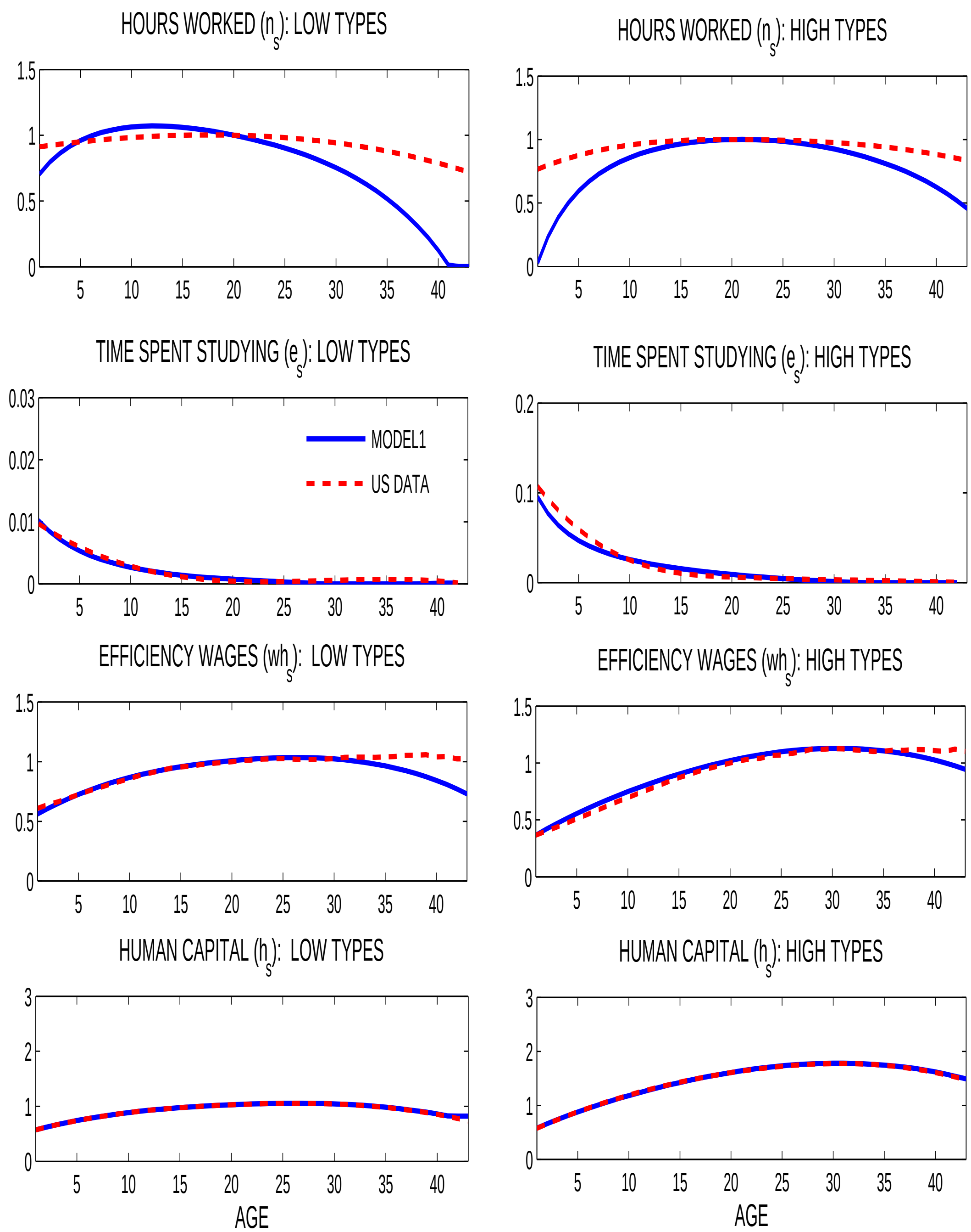


Figure 2.2: Life-cycle profiles Model2

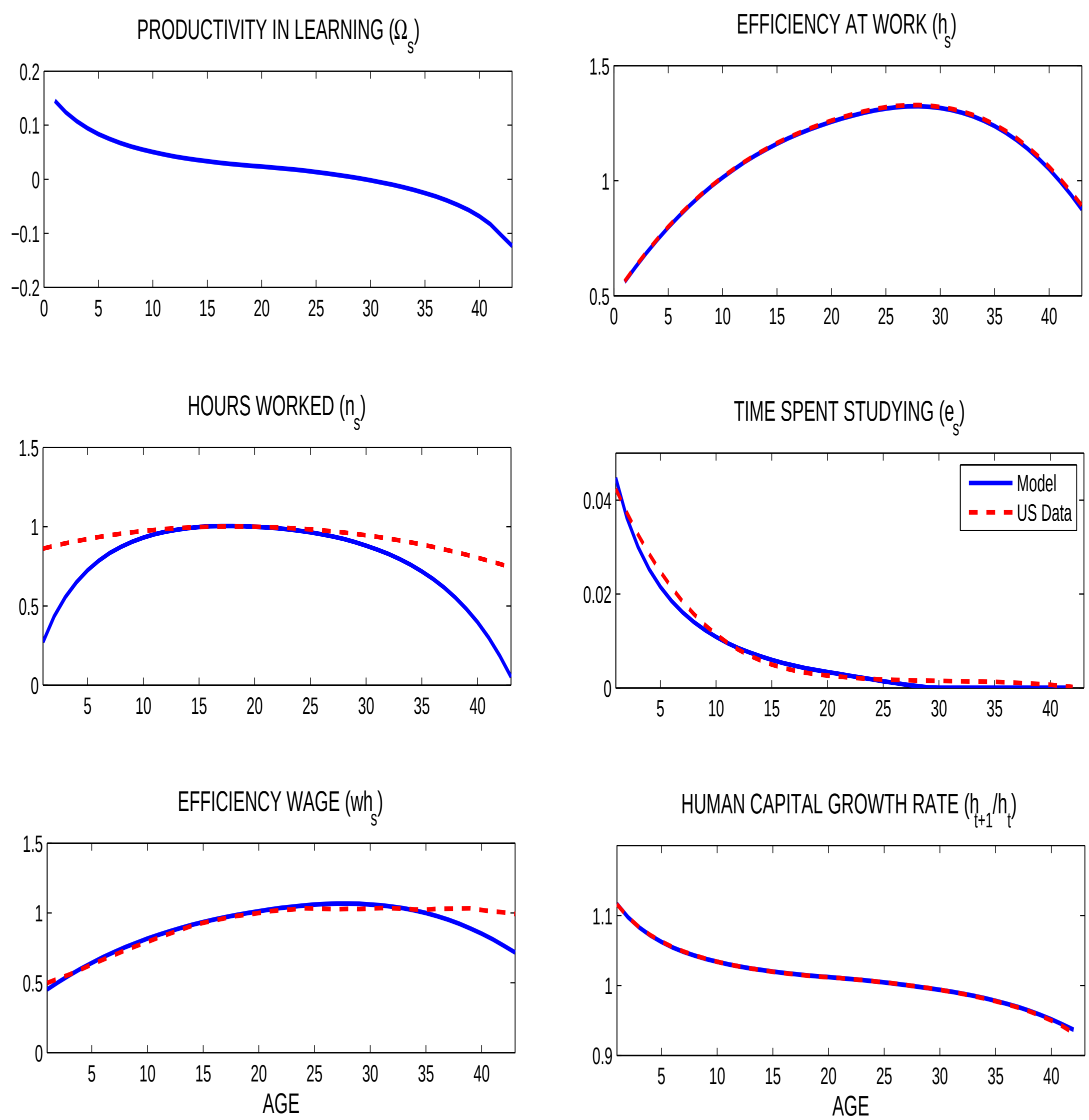


Figure 2.3: Impulse response functions Model1

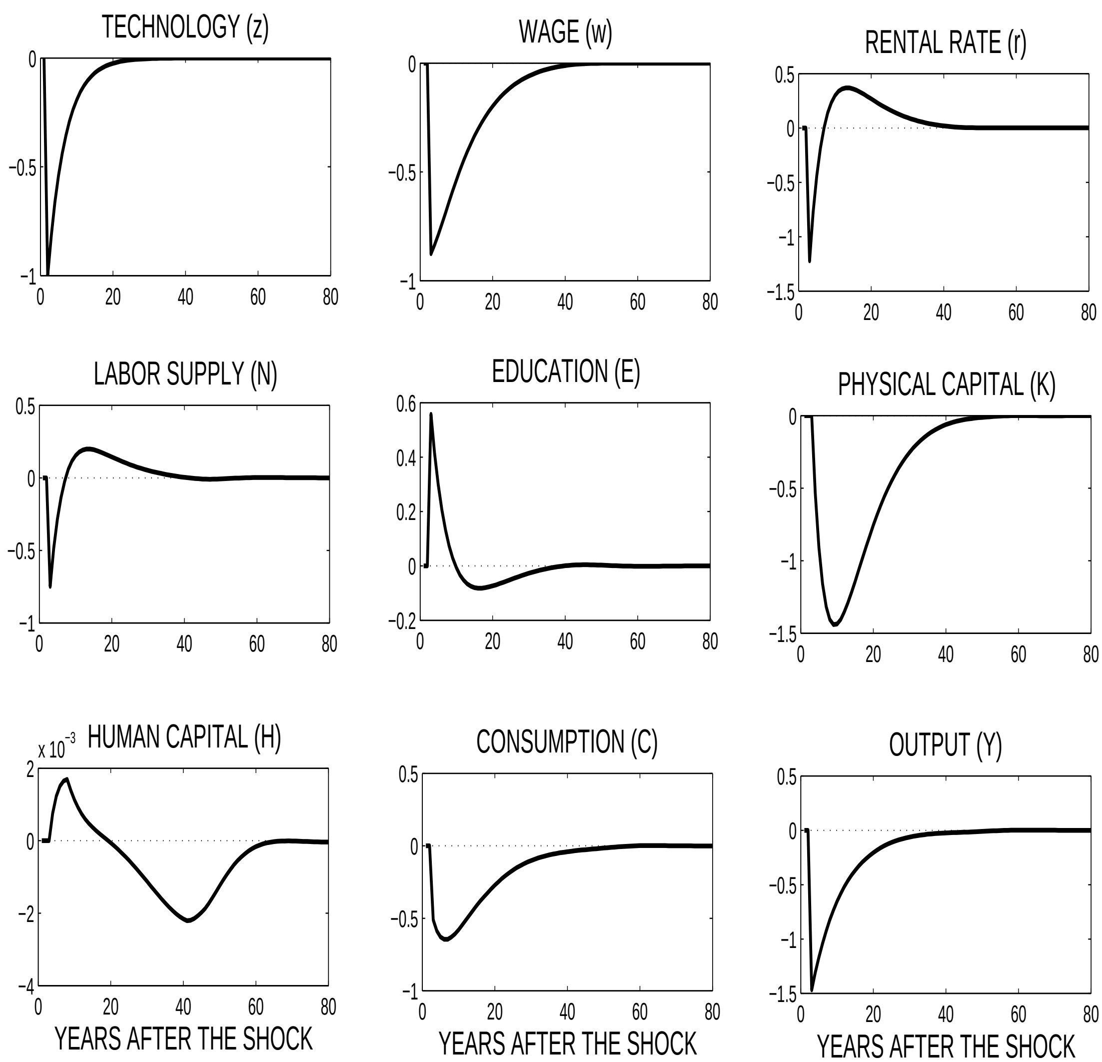
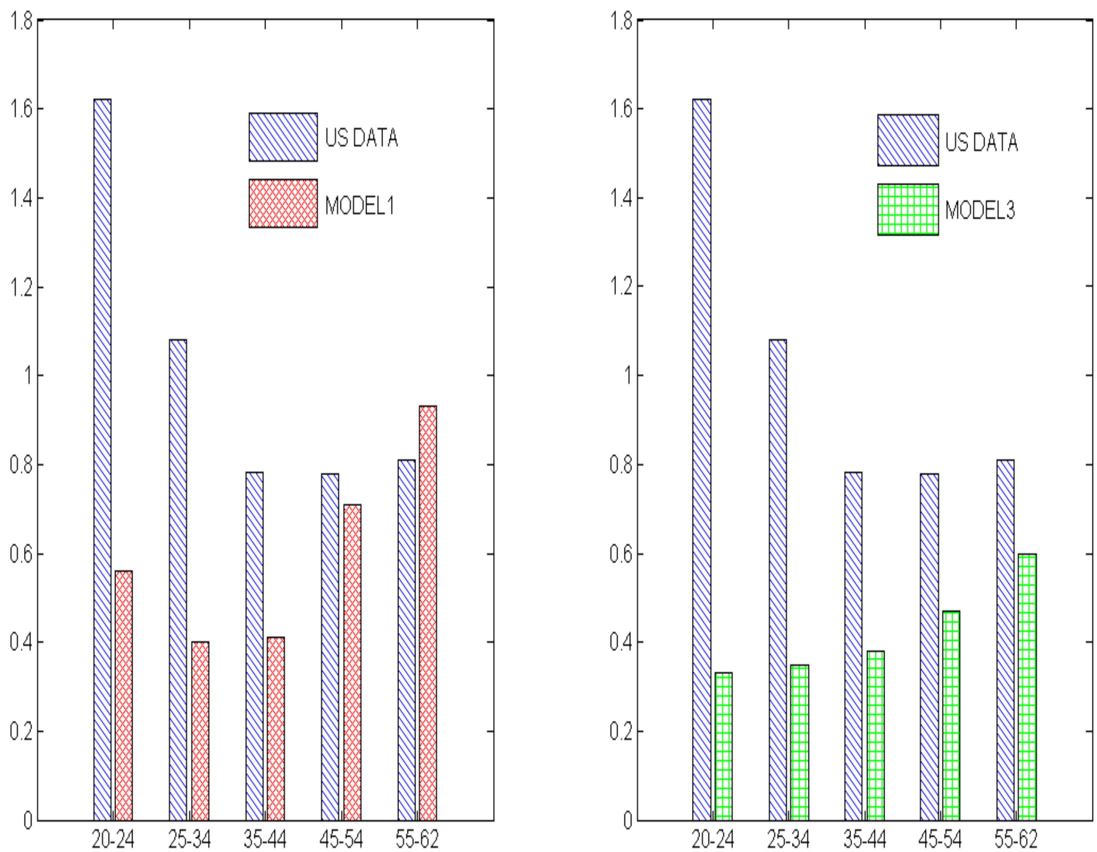


Figure 2.4: Volatility profile for hours worked



The x-axis refers to the age group. The y-axis refers to the labor supply volatility.

Figure 2.5: Life-cycle profiles Model4

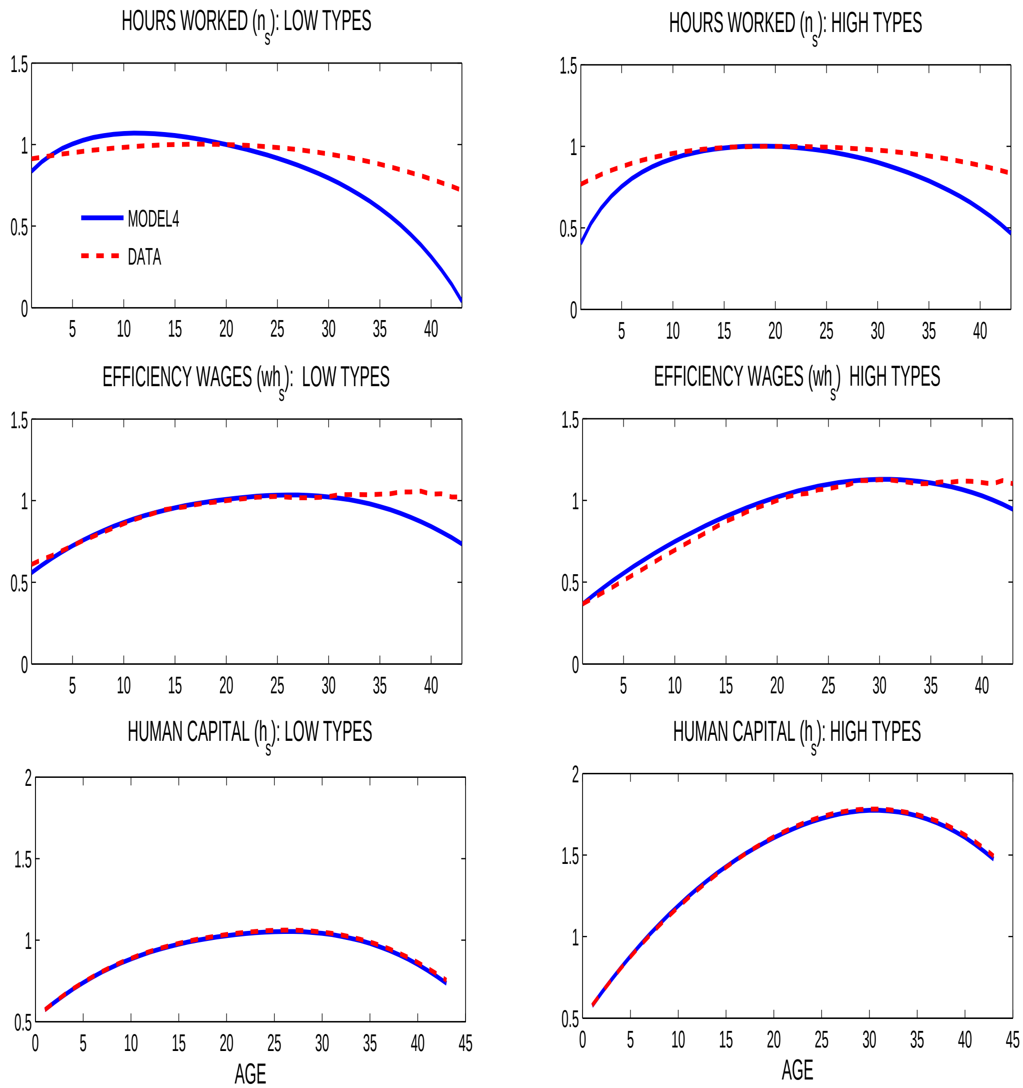


Figure 2.6: Life-cycle profiles of low types for different *sub* values

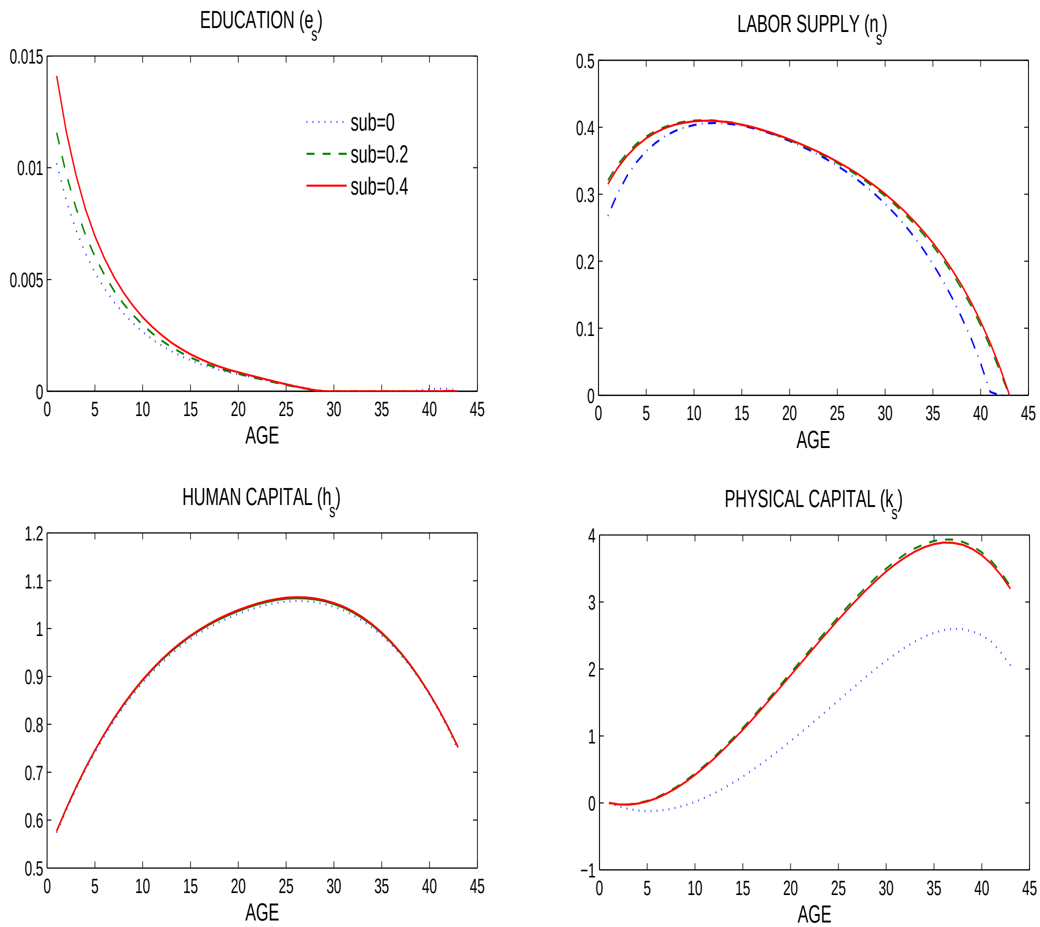


Figure 2.7: Life-cycle profiles of high types for different *sub* values

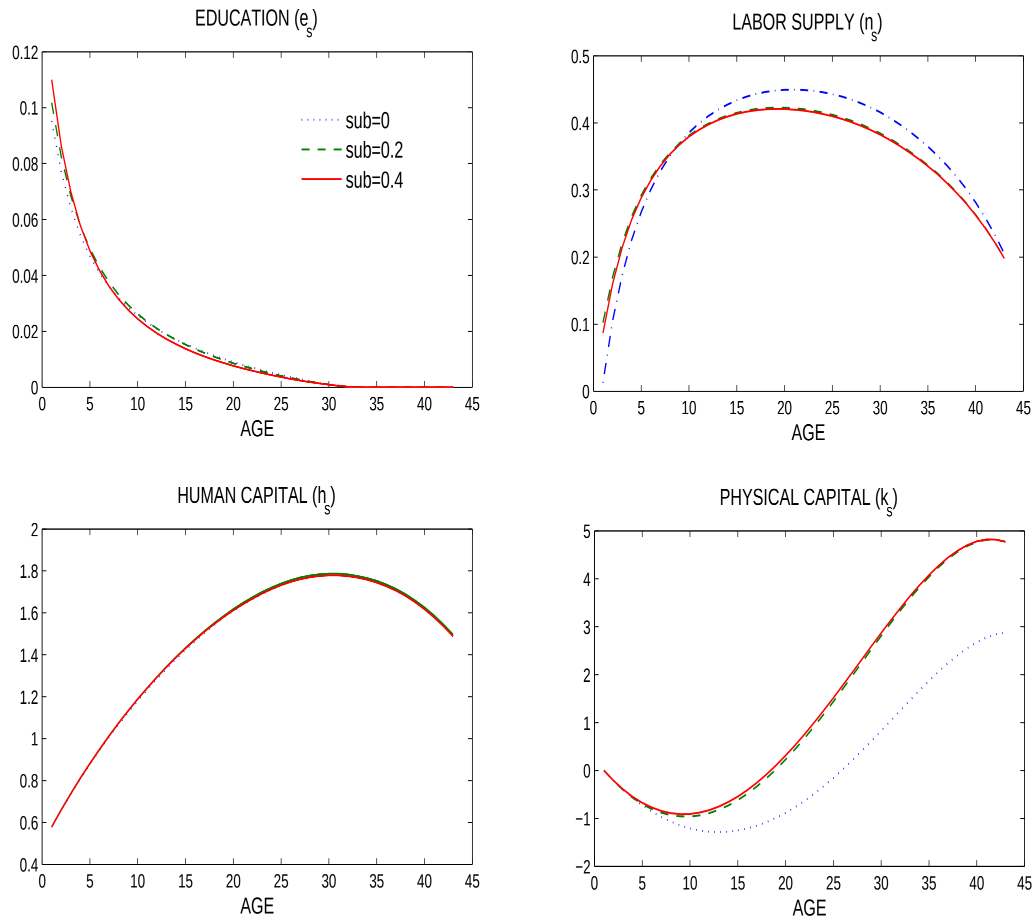


Figure 2.8: The impact of (acyclical) subsidies on education

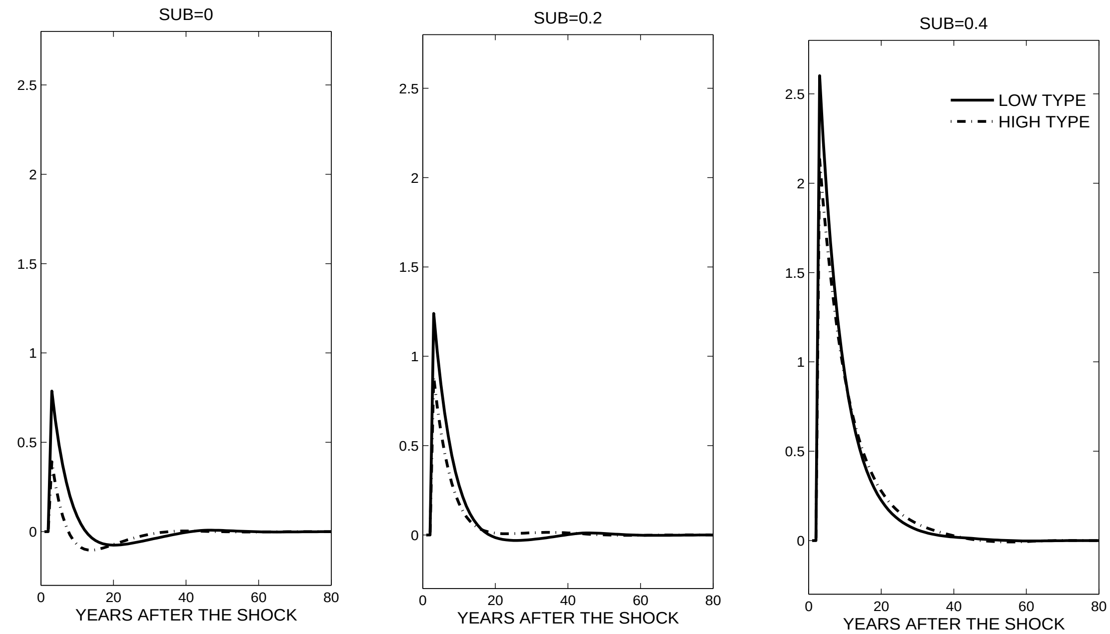


Figure 2.9: The impact of (pro-cyclical) subsidies on education

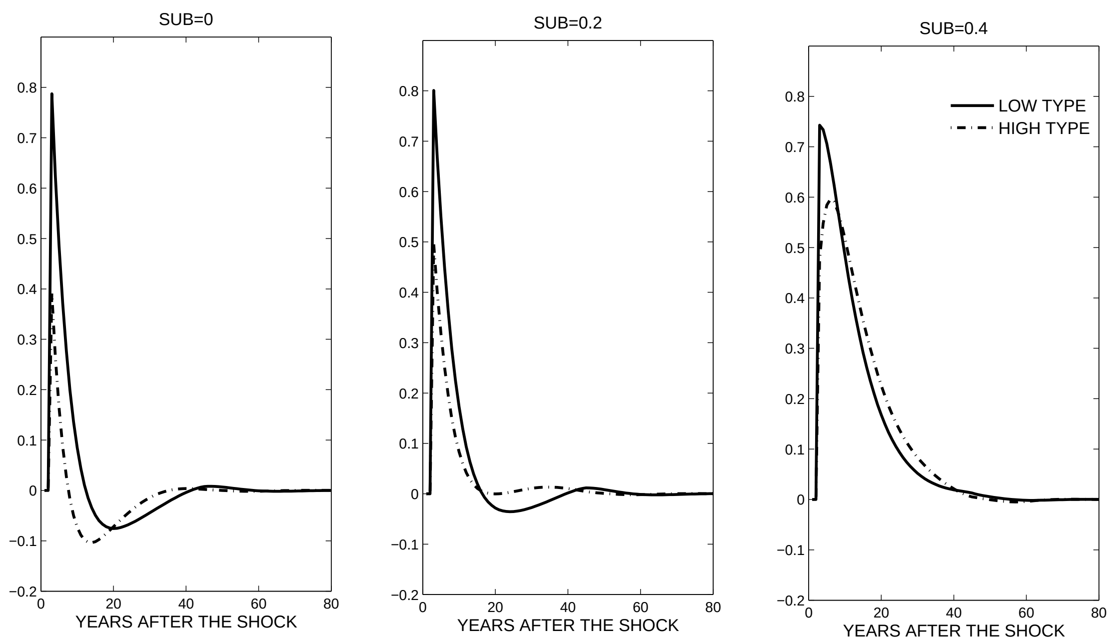
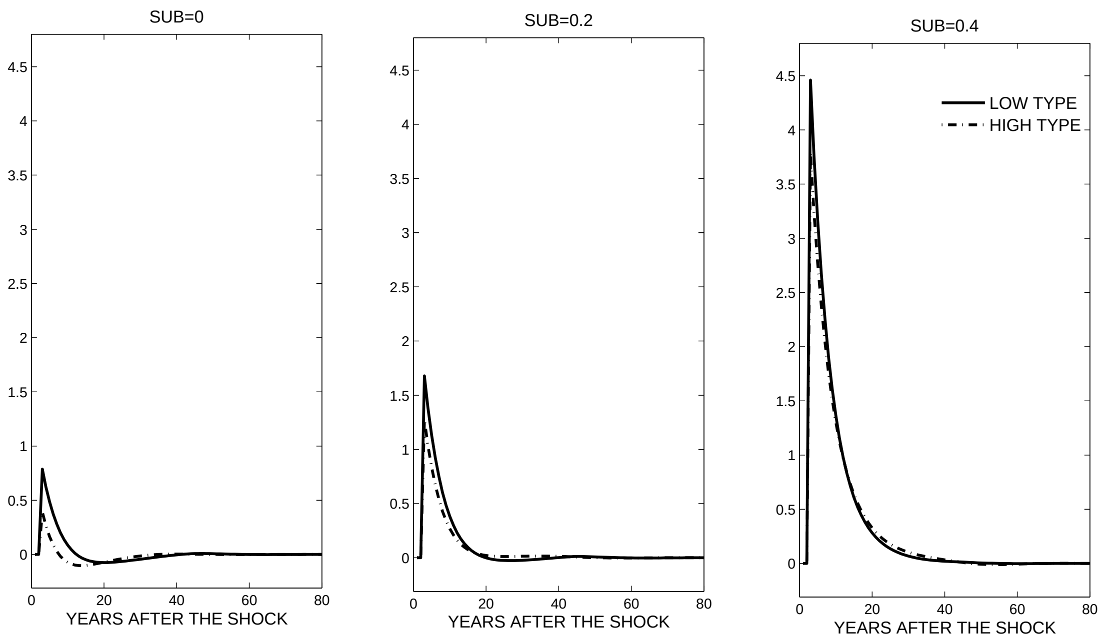


Figure 2.10: The impact of (counter-cyclical) subsidies on education



Appendix

Household's maximization problem:

$$max \qquad E_t \sum_{s=1}^{S_{max}} \beta^{s-1} \psi_s \left[\frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma}\right)^{1-\eta}}{1-\eta} \right]$$

by choosing $\{c_{s,t,i}\}_{s=1}^{S_{max}}, \{n_{s,t,i}\}_{s=1}^{S_r-1}, \{e_{s,t,i}\}_{s=1}^{S_r-2}, \{k_{s+1,t+1,i}\}_{s=1}^{S_{max}}, \{h_{s+1,t+1,i}\}_{s=1}^{S_r-1}$

subject to

$k_{s+1,t+1,i} = (1 + r_t - \delta)k_{s,t,i} + (1 - \tau_t)w_t n_{s,t,i} h_{s,t,i} - c_{s,t,i} + sub * z_t^a e_{s,t,i}^d + tr_t - T_t,$

($s = 1 : S_r - 1$)

$k_{s+1,t+1,i} = (1 + r_t - \delta)k_{s,t,i} + b_t - c_{s,t,i} + tr_t - T_t,$ ($s = S_r : S_{max}$)

$h_{s+1,t+1,i} = h_{s,t,i}(1 - \delta_h) + \Omega_{s,i} h_{s,t,i} e_{s,t,i}^{\phi_i},$ ($s = 1 : S_r - 1$)

$e_{s,t,i} + n_{s,t,i} + m_{s,t,i} = 1$

$e_{s,t,i} \geq 0$, $n_{s,t,i} \geq 0$, $m_{s,t,i} \geq 0$

$m_{s,t,i} = 1$, $n_{s,t,i} = 0$ for $s = S_r : S_{max}$

The value function is given by:

$s = 1 : S_r - 1$

$$\begin{aligned} V(k_{s,t,i}, h_{s,t,i}) = {} & \frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma}\right)^{1-\eta}}{1-\eta} + \beta \psi_{s+1} E_t V(k_{s+1,t+1,i}, h_{s+1,t+1,i}) \\ & + \lambda_{s,t,i}[(1 + r_t - \delta)k_{s,t,i} + (1 - \tau_t)w_t n_{s,t,i} h_{s,t,i} - c_{s,t,i} - k_{s+1,t+1,i} \\ & + sub * z_t^a e_{s,t,i}^d + tr_t - T_t] + \mu_{s,t,i}[\Omega_{s,i} h_{s,t,i} e_{s,t,i}^{\phi} - h_{s+1,t+1,i} \end{aligned}$$

$$+ h_{s,t,i}(1-\delta_h)] \tag{2.11}$$

$s = S_r : S_{max}$

$$V(k_{s,t,i}) = \frac{(c_{s,t,i})^{1-\eta}}{1-\eta} + \beta\psi_{s+1}E_tV(k_{s+1,t+1,i})$$

$$+ \lambda_{s,t,i}[(1+r_t-\delta)k_{s,t,i} + b_t - c_{s,t,i} - k_{s+1,t+1,i} + tr_t - T_t] \tag{2.12}$$

First order conditions:

$s = 1 : S_r - 1$

$$w.r.t.\ c_{s,t,i}: \quad \lambda_{s,t,i} = c_{s,t,i}^{-\eta} m_{s,t,i}^{\gamma(1-\eta)} \tag{2.13}$$

$$w.r.t.\ n_{s,t,i}: \quad \lambda_{s,t,i} = \frac{\gamma c_{s,t,i}^{1-\eta} m_{s,t,i}^{\gamma(1-\eta)-1}}{(1-\tau_t)w_t h_{s,t,i}} \tag{2.14}$$

$$w.r.t.\ k_{s+1,t+1,i}: \quad \lambda_{s,t,i} = \beta E_t V_k(k_{s,t,i}, h_{s,t,i}) = \beta E_t \lambda_{s+1,t+1,i}(1+r_{t+1}-\delta) \tag{2.15}$$

$$w.r.t.\ e_{s,t,i}: \quad \gamma c_{s,t,i}^{1-\eta} m_{s,t,i}^{\gamma(1-\eta)-1} = \mu_{s,t,i}\phi_i\Omega_{s,i}h_{s,t,i}e_{s,t,i}^{\phi_i-1} \tag{2.16}$$

$$+ \lambda_{s,t,i} sub * dz_t^a e_{s,t,i}^{d-1} \tag{2.17}$$

$$w.r.t.\ h_{s+1,t+1,i}: \quad \mu_{s,t,i} = \beta E_t V_h(k_{s,t,i}, h_{s,t,i}) = \beta E_t[\lambda_{s+1,t+1,i}(1-\tau_{t+1})w_{t+1}n_{s+1,t+1,i}]$$

$$+ \beta E_t \mu_{s+1,t+1,i}[\Omega_{s+1,i}e_{s+1,t+1,i}^{\phi_i} + (1-\delta_h)] \tag{2.18}$$

$s = S_r : S_{max}$

$$w.r.t.\ c_{s,t,i}: \quad \lambda_{s,t,i} = c_{s,t,i}^{-\eta} \tag{2.19}$$

$$w.r.t.\ k_{s+1,t+1,i}: \qquad \lambda_{s,t,i} = \beta E_t \lambda_{s+1,t+1,i}(1 + r_{t+1} - \delta) \tag{2.20}$$

Firm's maximization problem:

$$\max_{K_t, L_t} \qquad \Pi_t = z_t K_t^{\alpha} L_t^{1-\alpha} - wL_t - rK_t$$

First order conditions:

$$w_t = (1-\alpha) z_t K_t^{\alpha} {L_t}^{-\alpha} \tag{2.21}$$

$$r_t = \alpha z_t K_t^{\alpha-1} L_t^{1-\alpha} \tag{2.22}$$

Household's maximization problem in Model3:

$$max \qquad E_t \sum_{s=1}^{S_{max}} \beta^{s-1} \psi_s \left[\frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma}\right)^{1-\eta}}{1-\eta} \right]$$

by choosing $\{c_{s,t,i}\}_{s=1}^{S_{max}}$, $\{n_{s,t,i}\}_{s=1}^{S_r-1}$, $\{k_{s+1,t+1,i}\}_{s=1}^{S_{max}}$

subject to

$k_{s+1,t+1,i} = (1 + r_t - \delta)k_{s,t,i} + (1 - \tau_t)w_t n_{s,t,i} - c_{s,t,i} + tr_t$, $(s = 1 : S_r - 1)$

$k_{s+1,t+1,i} = (1 + r_t - \delta)k_{s,t,i} + b_t - c_{s,t,i} + tr_t$, $(s = S_r : S_{max})$

$n_{s,t,i} + m_{s,t,i} = 1$

$n_{s,t,i} \geq 0$, $m_{s,t,i} \geq 0$

$m_{s,t,i} = 1$, $n_{s,t,i} = 0$ for $s = S_r : S_{max}$

The value function is given by:

$s = 1 : S_r - 1$

$$V(k_{s,t,i}) = \frac{\left(c_{s,t,i} m_{s,t,i}^{\gamma}\right)^{1-\eta}}{1-\eta} + \beta\psi_{s+1} E_t V(k_{s+1,t+1,i})$$
$$+ \lambda_{s,t,i}[(1 + r_t - \delta)k_{s,t,i} + (1 - \tau_t)w_t n_{s,t,i} - c_{s,t,i} - k_{s+1,t+1,i} + tr_t] \tag{2.23}$$

$s = S_r : S_{max}$

$$V(k_{s,t,i}) = \frac{(c_{s,t,i})^{1-\eta}}{1-\eta} + \beta\psi_{s+1} E_t V(k_{s+1,t+1,i})$$
$$+ \lambda_{s,t,i}[(1 + r_t - \delta)k_{s,t,i} + b_t - c_{s,t,i} - k_{s+1,t+1,i} + tr_t] \tag{2.24}$$

First order conditions:

$s = 1 : S_r - 1$

$$w.r.t.\ c_{s,t,i}: \qquad \lambda_{s,t,i} = c_{s,t,i}^{-\eta} m_{s,t,i}^{\gamma(1-\eta)} \tag{2.25}$$

$$w.r.t.\ n_{s,t,i}: \qquad \lambda_{s,t,i} = \frac{\gamma c_{s,t,i}^{1-\eta} m_{s,t,i}^{\gamma(1-\eta)-1}}{(1-\tau_t)w_t} \tag{2.26}$$

$$w.r.t.\ k_{s+1,t+1,i}: \qquad \lambda_{s,t,i} = \beta E_t V_k(k_{s,t,i}) = \beta E_t \lambda_{s+1,t+1,i}(1 + r_{t+1} - \delta) \tag{2.27}$$

$$(2.28)$$

$s = S_r : S_{max}$

$$w.r.t.\ c_{s,t,i} : \qquad \lambda_{s,t,i} = c_{s,t,i}^{-\eta} \tag{2.29}$$

$$w.r.t.\ k_{s+1,t+1,i} : \qquad \lambda_{s,t,i} = \beta E_t \lambda_{s+1,t+1,i}(1 + r_{t+1} - \delta) \tag{2.30}$$

Chapter 3

On the cyclicality of schooling decisions: Evidence from Canadian data

3.1 Introduction

This paper investigates how business cycles impact post-secondary education (PSE) decisions. The literature has already analyzed the response of college enrollment to economic cycles, providing inconsistent empirical results. On one hand, economic downturns stimulate PSE enrollment by reducing the opportunity cost of education (i.e. the forgone labor income). On the other hand, recessions negatively affect family income and reduce the ability to afford education. The cyclicality of PSE enrollment depends on which effect dominates.

Economic downturns have negative consequences on the economy in the short run.

However, if enrollment rates are counter-cyclical, crises may also have a positive impact on the economy. Several studies have shown the importance of human capital for growth starting from the seminal paper by Mankiw et al. (1992). Education also generates other types of positive externalities (e.g. reduced crime and increased civic participation. For an overview, see Hanushek and Woessmann 2008). If individuals acquire more skills and knowledge during recessions, the economy may benefit both in the short and long run.

The long-run economic impact of recession is perhaps the most interesting and least explored aspect. If downturns increase the total stock of human capital and human capital fosters technological progress, economic crises may have a positive long-run impact on the economy. The literature has shown that recessions lead to the re-organization and destruction of the least productive firms and, therefore, may affect productivity (Caballero and Hammour, 1994, 1996; Hall, 2000). However, the impact of economic crises on productivity may also depend on the counter-cyclicality of education and human capital accumulation. This does not imply that recessions are beneficial for the economy. The costs of recessions most likely offset the benefits. However, it is still important to have a comprehensive picture of the dynamics associated with economic downturns.

Several papers have analyzed the cyclicality of college enrollment using U.S. data. Mattila (1982), Polzin (1984), Kane (1994), Edwards (1976) and Christian (2007) found no impact of business cycles on enrollment decisions. Betts and McFarland (1995), Dellas and Sakellaris (2003), Dellas and Koubi (2003), and Méndez and Sepúlveda (2012) found evidence in favor of counter-cyclicality. Sakellaris and Spilimbergo (2000) focused on US enrollment rates of foreign students. They found a negative relationship between US enrollment rates of foreign students coming from OECD countries and GDP growth in the country of origin. However, the relationship is positive for students coming from non-OECD countries. This result suggests that enrollment is pro-cyclical in countries where the financial support to PSE is low and access to credit is restricted, such as non-OCED countries. In this case, it is difficult for students to afford education during economic contractions.

Instead, Brunello and Winter-Ebmer (2003) focused on the time to degree using European data. By looking at 26 economics and business faculties in 10 European countries, they show that the average excess time to graduation is positively correlated with unemployment. The literature has also studied the cyclicality of other types of human capital accumulation, such as job training. In the US, for example, training financed by employees is counter-cyclical, while training sponsored by firms is pro-cyclical (Méndez and Sepúlveda, 2012).

However, with the exception of Emery et al. (2012), little work has been done regarding PSE decisions in Canada. In their paper, Emery and co-authors study the impact that the natural resource boom in Alberta in the 80s had on human capital accumulation. They show that, on average, young individuals postponed post-secondary education and entered the labor market after completing high school in order to take advantage of high salaries in the oil industry.

The current paper, instead, is the first study that uses Canadian data from all provinces

(Survey of Labor and Income Dynamics, SLID) and provides a complete analysis of PSE-related decisions. Further, the analysis distinguishes between individuals of different ability levels, which is new to the literature. The importance of using Canadian data is twofold. First, the education systems in Canada and US present some differences. Also the government intervention in the education sector varies between the countries. Therefore, there is no reason to assume that the results found in the US apply to Canada as well. Second, the majority of previous studies in the literature focused on college enrollment by using cross-sectional data[1]. By using panel data from SLID, instead, this paper provides a complete analysis of PSE decisions, including the decision to pursue graduate studies, the decision to drop out of university, and the decision to leave the labor market and return to school.

Main results show that university enrollment is counter-cyclical: more people enroll in university during economic contractions. Business cycles mainly affect decisions of recent high-school graduates. Recessions do not seem to have a significant impact on the decision to pursue graduate studies or the decision to leave the labor market to return to university. Ability, proxied by parental education, negatively affects the counter-cyclicality of university enrollment. This result is very interesting because it may have important implications on income inequality. Since recessions mainly stimulate university enrollment of low-ability individuals, economic contractions may have a positive impact on the earnings differential of low-ability versus high-ability individuals. This aspect is unexplored in the current literature.

[1]The only exceptions are Méndez and Sepúlveda (2012), who used panel data from NLSW and focused mainly on training activities, and Brunello and Winter-Ebmer (2003) who analyzed time to degree using European data.

Finally, economic downturns stimulate the acquisition of theoretical rather than practical/job oriented education. In fact, contrary to university enrollment, college enrollment is pro-cyclical and enrollment in other (non-university) PSE institutions is acyclical.

The paper is organized as follows. An overview of the dataset used for the analysis is reported in Section 3.2. Section 3.3 discusses the methodology and the results. Finally, Section 3.4 concludes by summarizing the main findings and directions for future research.

3.2 Data

This paper uses confidential data from SLID (1993-2010). This is a longitudinal survey started in 1993. Individuals are followed for six consecutive years. A new panel is introduced every three years. Each panel includes approximately 17,000 individuals. The survey targets all individuals living in Canada, excluding residents of the Territories and Indian reserves. Starting from 2011, the survey is no longer longitudinal.

From SLID, I construct a pooled panel sample (1993-2010) by pooling together panels 1 through 6[2]. Since the focus is on post-secondary education decisions, I exclude from the sample individuals who never graduated from high school. I collect information about school attendance, employment status, as well as age, ethnicity, sex, parental education, family resources (e.g. house ownership, family income and family size) and residence. After dropping observations where the respondent has missing information on educational

[2]Panel 1 reference years: 1993-1998), panel 2 reference years: 1996-2001, panel 3 reference years: 1999-2004, panel 4 reference years: 2003-2007, panel 5 reference years: 2005-2010 and panel 6 reference years: 2007-2010.

activity, the sample contains 609,744 observations. Summary statistics are reported in Table 3.1.

Following the classification in SLID, I distinguish among the following post-secondary education institutions: university (ISCED[3] 5A and 6); college (ISCED 5B); trades, business and commercial schools (ISCED 4). For each category, I create a dummy variable that indicates whether the respondent was enrolled in any of these institutions during the reference year. From SLID, I also construct a series of variables that have an important impact on schooling decisions: the number of high school graduates in a given year and the PSE premium computed as log-difference between earnings of post-secondary graduates and high-school graduates.

To the dataset, I add the following aggregate variables obtained from Statistics Canada and the World Bank: annual provincial unemployment rate, annual provincial GDP, annual provincial employment rate, real interest rate, average weekly earnings, and the weighted national tuition level at public universities for domestic students enrolled in undergraduate programs. The first three variables are used as alternative indicators of business cycle fluctuations.

On average, individuals in the sample are 39 years old, married and live in urban areas. 13% of the individuals are enrolled in post-secondary education. Specifically, 6% are in university, 4% are in college, 1% are in CEGEP[4] and 2% are enrolled in other programs (i.e. trades, business schools).

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[3]ISCED is the International Standard Classification of Education developed by UNESCO.

[4]Collge d'enseignement gnral et professionnel in Quebec.

Cyclicality of enrollment rates

The cyclical behavior of enrollment rates in post-secondary education is reported in Figure 3.1. Figure 3.2, instead, disaggregates enrollment by PSE institution (i.e. university and college). Other types of PSE institutions present a similar pattern. Enrollment rates are obtained from the Labour Force Survey (October, 1976-2012), while the annual GDP series (1976-2012) is obtained from the World Bank. Both series are detrended using an HP filter with a smoothing parameter equal to 6.25. The correlation coefficient between GDP and enrollment rates is -0.35, -0.28 and -0.24 for PSE, university and college, respectively. In all three cases, enrollment rates display a counter-cyclical pattern. More students are enrolled when the GDP level of the economy is below trend. The next section investigates the cyclicality of schooling decisions at the micro level.

3.3 Methodology and Results

The probability of being enrolled in post-secondary education can be estimated by:

$$Pr(enrolled_{it} = 1/X_{i,t}) = F(\alpha + \beta X_{i,t}) \tag{3.1}$$

where $enrolled_{it}$ is a dummy variable equal one if individual i is enrolled in a PSE institution at time t and zero otherwise, F is a logistic transformation of the linear index function $(\alpha + \beta X_{i,t})$, $X_{i,t}$ is a vector including individual characteristics (i.e. demographic variables, geographic variables, family resources, parental education) and aggregate variables that affect schooling decisions (i.e. real interest rate, university tuition[5], average weekly earnings, PSE premium, high-school graduates and the cyclical indicator).

I assume the following structure for the error term:

$$u_{i,t} = \alpha_i + \epsilon_{i,t} \tag{3.2}$$

where $\epsilon_{i,t}$ is i.i.d.. In order to take into account unobserved individual characteristics (α_i), equation 3.1 is estimated using a conditional logistic regression:

$$Pr(enrolled_{it} = 1/\alpha_i, X_{i,t}) = F(\alpha_i + \beta X_{i,t}). \tag{3.3}$$

This type of regression is different from an ordinary logistic regression because the data are divided into groups (in this case, individuals) and within each group the probability of a positive outcome (e.g. enrollment) is partly determined by unobserved individual characteristics (i.e. fixed effects). Further, terms that are constant within groups cannot be estimated by this regression. This implies that it is not possible to estimate the intercepts (i.e. fixed effects), the effect of other constant observed factors (e.g. gender, ethnic background) and average marginal effects. By performing a Hausman test, I reject the null that the coefficients in the fixed-effects and random-effects models are the same[6].

Table 3.2 reports the logit coefficients form the estimation in equation 3.3. Robust stan-

[5]Given the unavailability of data on tuition for college and trades, university tuition is used as proxy for tuition in any PSE institution.

[6]χ^2=249.82, Prob $> \chi^2$= 0.000.

dard errors are in parenthesis. *Ceteris paribus*, family resources have a significant impact on the log odds of enrollment. Family income increases the log odds of being enrolled. The number of earners has a similar effect. Living at home with parents and working[7] increase the log odds of being enrolled. Tuition has a positive but non always significant impact. This result is consistent with previous studies on university enrollment in Canada. The literature has not consistently found a negative relationship between university tuition and university enrollment. See Neill (2009) for an overview of Canadian studies. This result is also consistent with US studies by Dellas and Sakellaris (2003) and Betts and McFarland (1995).

The effect of the number of high-school graduates depends on the PSE institution. This variable is included in the regression to partially account for the probability of being admitted into a PSE program. The likelihood of enrollment decreases as the number of applications increases. The number of applications, in turn, depends on the number of high-school graduates. Therefore, the coefficient should be negative (competition effect). However, the number of high-school graduates can also account for signaling effects. If there are many graduates from high school, on average, students have an incentive to enroll in PSE rather than entering the labor market in order to signal their ability. In this case, the coefficient should be positive. Since the logit coefficient is insignificant for university enrollment, the two effects offset each other in this case. This is in accordance with the results in Dellas and Sakellaris (2003) and Mattila (1982). However, the competition effect dominates

[7]Working refers to any type of work (full-time or part-time).

the signaling effect for enrollment in trade schools, while the opposite is true for college enrollment.

Also the cyclicality of PSE enrollment depends on the type of institution. University enrollment is counter-cyclical, while college enrollment is pro-cyclical. Enrollment in other institutions (e.g. trades, commercial and business schools) is acyclical. Overall, PSE enrollment is acyclical as well. Table 3.4 shows the robustness of these results to different cyclical indicators. Marginal effects (at the means) are reported in squared brackets. In an ordinary logit model, the marginal effect of variable x is given by: $\widehat{F(\cdot)}\left(1-\widehat{F(\cdot)}\right)\beta_x$, where $\widehat{F}$ is the sample counterpart of F. However, in a conditional logit model, $\widehat{F}$ cannot be estimated unless we assume that the intercept is zero (i.e. fixed effect is zero). This assumption would contradict the reason why we use a conditional logit model in the first place. As a result, I replace $\widehat{F}$ with the sample mean of the dependent variable. This implies that $\widehat{F}$ is the same for all individuals.

As shown in the table, GDP and employment rates have a negative impact on the probability of being enrolled in university, while unemployment has a positive impact on university enrollment. For example, the marginal effect of unemployment indicates that a one-unit increase in the unemployment rate increases the probability of being enrolled in university by one percentage point. This implies that enrollment in Canadian universities is counter-cyclical, which is consistent with the results discussed in Chapter 1. On the contrary, college enrollment is pro-cyclical. This result has important implications on the type of human capital that individuals accumulate during business cycles. Recessions stimulate the acquisition of general education rather than practical/job-oriented education. During expansionary periods, instead, the opposite is true. A possible explanation is related to the fact that university graduates earn higher salaries and face lower unemployment rates on average. During difficult times, students may be more sensitive to differences among PSE institutions in terms of returns to schooling. Therefore, they may be more oriented towards university rather than college education because the former offers better prospects and a better insurance against future recessions.

Differences by ability type

Tables 3.6 through 3.9 present the results for different ability types. Parental education is used as a proxy for ability. This is common in the economics of education literature and reflects the fact that ability is both inherited and created. Besides genetics, ability greatly depends on early human capital investments made by parents on behalf of their children, family income and the parental environment[8]. For these reasons, parental education is a strong predictor of an individual's educational achievement and it is often used as proxy for ability. Tables 3.6 and 3.7 show the results using father's education, Tables 3.8 and 3.9 shows the results using mother's education.

Given the ability measure used in this chapter, the cyclicality of university enrollment is mainly driven by low-ability individuals. Enrollment is acyclical for high types in all cases. These results are consistent with the empirical analysis discussed in Chapter 1. The differ-

[8]For a review of the empirical and theoretical studies on this topic, see Cunha et al. (2006) and Carneiro and Heckman (2003).

ence in behavior between ability types can be explained by differences in the opportunity cost and the benefit of education. On average, high types are more productive in learning. Their benefit of education is high and is likely to offset the cost. Therefore, they are more likely to attend PSE compared to low types during normal times. As a result, their schooling decisions are not significantly affected by business cycles. They enroll independently of the state of the economy. On the contrary, low types are less likely to attend university or college during normal times because the cost is higher than the benefit. Therefore, business cycles have an impact on their decisions. When a downturn hits the economy, the opportunity cost of leaving the labor market or reducing labor supply is lower and the opportunity cost of education decreases. This is especially true for low types. Labor market conditions tend to be worse for low-ability individuals who earn lower salaries, face fewer opportunities for promotion and career development, and face higher unemployment rates. Therefore, they are more likely to give up labor market opportunities and enroll in university, which may explain why their enrollment is counter-cyclical. Regarding enrollment in other institutions, the results do not display a consistent difference between ability types. This could be explained by the fact that low types are likely to attend college or trade schools during normal times. Therefore, their decisions are not affected by macroeconomic conditions.

Employment-to-school transition

The panel structure of SLID allows me to further investigate people's decisions regarding post-secondary education. This section focuses on the transition from work to school. Do people leave the labor market to enroll in PSE during recessions? Or do recessions affect only students who are graduating from high school and are about to decide on post-secondary education?

Table 3.10 shows the logit coefficients obtained from a conditional logistic regression that estimates the odds of leaving the labor market to return to school. The dependent variable is a binary variable equal one if the respondent worked for at least 20 weeks during the previous year and is enrolled in university/college/trade school during the current year. The dependent variable is equal zero if the respondent worked for at least 20 weeks in the previous year and is not enrolled in the current year. There is no evidence to support the claim that individuals are likely to return to school during bad times. Therefore, business cycles mainly impact PSE decisions of recent high-school graduates or who is already enrolled in a post-secondary program. However, there is some evidence suggesting that workers go back to school to pursue a college degree during economic expansions. This result is consistent with the findings in King and Sweetman (2002), who showed that skill retooling is pro-cyclical for Canadian workers over 25 years old. Skill retooling refers to the decision to return to school in order to acquire new skills and switch occupation.

University enrollment: differences by major and degree

This section focuses on university enrollment and distinguishes among university majors and degrees. For the purpose of this analysis, university major has been grouped into six categories: humanities, arts, social sciences; business; physical and life sciences, mathematics, computer and information sciences, and engineering; agriculture and natural resources; health and fitness; personal, protective and transportation services, and others[9]. As shown by Table 3.11, enrollment in humanities, sciences and agricultural studies is counter-cyclical, while enrollment in other programs is acyclical with the exception of group 6.

Table 3.12, instead, compares respondents with and without bachelor's degree. Enrollment is counter-cyclical only for respondents without a bachelor's degree. Therefore, business cycles mainly affect the decision to pursue a first degree rather than the decision to pursue graduate studies or a second degree. This is consistent with the fact that macroeconomic conditions affect university enrollment decisions of recent high-school graduates only.

Does counter-cyclical enrollment lead to a higher number of university graduates?

Do students, who initially enrolled due to the recession, complete their studies? This question is important because, if students graduate at the end of their studies, economic

[9]This classification is based on the Classification of Instructional Programs (CIP)- primary grouping developed by Statistics Canada and the National Centre for Education Statistics. The six categories have been defined as follows: group 1 (CIP -primary grouping 1-4), group 2 (CIP -primary grouping 5), group 3 (CIP -primary grouping 6-8), group 4 (CIP -primary grouping 9), group 5 (CIP -primary grouping 10), group 6 (CIP -primary grouping 11-12)

downturns also affect the total number of students with a PSE degree and, therefore, significantly impact the aggregate human capital stock in the economy. To answer this question, I construct a new binary variable equal one if the respondent was enrolled in the previous year and dropped from university in the current year, and zero if she is still enrolled in university. Then, I estimate the odds of dropping out of university using a conditional logistic regression. Together with the previous control variables, I include lags of GDP or lags of the difference between GDP in one year and the previous year. Based on the results presented in Table 3.13, the decision to drop out of university is not significantly affected by current economic conditions or economic conditions in previous years. Also changes in economic conditions from one year to another do not affect the odds to drop out. If the logit coefficients for GDP differences between consecutive years were positive and significant, students would be more likely to drop when economic conditions improve over time and less likely to drop when economic conditions worsen over time. Instead, insignificant coefficients suggest that students are likely to remain enrolled in university even if macroeconomic conditions improve while they are attending school.

Finally, Table 3.14 shows that if individuals adjust their schooling decisions during business cycles, they do so in a timely manner. The response to business cycles is immediate. Current economic conditions impact the probability of being enrolled, while economic conditions in previous years do not. This result holds for both university and college enrollment, and it is consistent with what Betts and McFarland (1995) found for the US.

3.4 Conclusions

This chapter has shown that PSE decisions respond to business cycles fluctuations. University enrollment is counter-cyclical, while college enrollment is pro-cyclical. This result suggests that economic contractions stimulate the acquisition of general education, while economic expansions stimulate the acquisition of practical and job-oriented education.

Low-ability individuals are driving the cyclicality of university enrollment. High-ability individuals are not responsive to macroeconomic conditions. Since they are more productive in learning, they tend to enroll in PSE during normal times. Further, once they enter the labor market, they earn higher wages and face lower unemployment rates on average. As a result, they do not benefit by leaving the labor market to accumulate extra skills and knowledge. There is no significant difference between ability types regarding college enrollment.

Macroeconomic conditions mainly affect the decision of recent high-school graduates to pursue a bachelor's degree, while they do not significantly affect the decision of older graduates to pursue advanced studies or return to university. In fact, there is little evidence suggesting that young workers leave the labor market in order to return to school during recessions. However, the decision to return to college is pro-cyclical, which is consistent with previous studies on the cyclicality of skill retooling.

If individuals respond to macroeconomic conditions by adjusting their schooling decisions, they do so in a timely manner. Consistent with US studies, the response is immediate. Finally, students are likely to remain enrolled even if macroeconomic conditions improve.

These results have important implications at the aggregate and individual level. Since, during economic downturns, individuals accumulate skills and knowledge that they would not acquire otherwise, recessions increase the aggregate human capital stock in the economy. This may positively impact the economy in the long run. Further, downturns may give the opportunity to low-ability individuals to reduce the earnings gap with high-ability individuals, suggesting that recessions may have a positive impact on income inequality. Both aspects have not been explored by the current literature, suggesting directions for future research.

Tables and Figures

Table 3.1: Summary statistics

Variable	Mean	Standard Deviation
Age	39.03	13.59
Female	0.51	0.50
Married	0.58	0.49
Single	0.27	0.45
PSE enrollment	0.13	0.33
University enrollment	0.06	0.24
College enrollment	0.04	0.19
CEGEP enrollment	0.01	0.12
Enrollment in other PSE institutions	0.02	0.13
Paid worker	0.76	0.43
Family size	3.12	1.39
House ownership	0.80	0.40
Resident in metropolitan area	0.75	0.43
Live with parents	0.68	0.47
N = 609,744		

Table 3.2: Logit coefficients: PSE enrollment

Dependent variable: PSE/university/college/other enrollment (=1 if enrolled, =0 otherwise)

	PSE enrolment		University enrolment		College enrolment		Enrolment in other institution	
GDP	3.21e-3	(2.04e-3)	-0.01*	(3.20e-3)	0.01***	(2.8e-3)	2.2e-3	(4.5e-3)
Age	0.42***	(0.03)	0.50***	(0.05)	0.41***	(0.04)	0.31***	(0.06)
Age^2	-0.01***	(0.00)	-0.01***	(0.00)	-0.01***	(0.00)	-0.01***	(0.00)
Married	-0.81***	(0.07)	-0.90***	(0.11)	-0.71***	(0.10)	-0.09	(0.13)
DSW	-0.79***	(0.10)	-0.90***	(0.19)	-0.70***	(0.13)	-0.08	(0.19)
Live in rural area	-0.20***	(0.105)	-0.24***	(0.09)	-0.10	(0.07)	-0.12	(0.09)
ln(family income)	0.63***	(0.03)	0.63**	(0.05)	0.41***	(0.05)	0.31***	(0.05)
Negative family income	-11.4***	(0.78)	-11.8***	(1.10)	-7.43***	(1.05)	-6.47***	(1.06)
Number of earners in hh	0.05***	(0.02)	0.12***	(0.03)	-0.01	(0.03)	-0.05	(0.03)
Live at home	1.18***	(0.06)	1.20***	(0.10)	0.81***	(0.08)	0.71***	(0.11)
Worked in ref. year	1.02***	(0.03)	1.21***	(0.05)	0.76***	(0.04)	0.44***	(0.06)
Real interest rate	-0.02**	(0.01)	-0.01	(0.16)	1.0e-3	(0.01)	-0.06***	(0.02)
University Tuition*1,000	0.06**	(0.02)	0.03	(0.04)	0.05	(0.04)	0.06	(0.06)
ln(high-school graduates)	0.09	(0.07)	0.04	(0.11)	0.24**	(0.11)	-0.29*	(0.15)
Average weekly earnings * 100	-0.03	(0.06)	0.25***	(0.09)	-0.16**	(0.08)	-0.20*	(0.12)
PSE premium	0.47	(0.42)	0.47	(0.67)	-0.37	(0.61)	2.12**	(0.83)
N	149,093		65,407		68,889		36,543	

Robust standard errors are reported in brackets. The weight variable used is *ilgwt26*. For each individual, I only use the weight in the first year the respondent joined the panel. GDP is in billions and has been detrended with an HP filter (smoothing parameter 6.25). Family income, tuition, GDP and average weekly earning are in 1993 constant dollars.
* 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Table 3.4: Logit coefficients and marginal effects: PSE enrollment

Dependent variable: PSE/university/college/other enrollment (=1 if enrolled, =0 otherwise)				
	PSE enrolment	University enrolment	College enrolment	Enrolment in other institution
GDP	3.2e-3	-0.01*	0.01***	2.2e-3
(standard error)	(2e-3)	(3.2e-3)	(2.8e-3)	(4.5e-3)
[marginal effect]	[4e-4]	[1e-3]	[4e-4]	[2e-5]
Controls	✓	✓	✓	✓
N	149,093	65,407	68,889	35,543
Unemployment rate	0.05*	0.16***	-0.03	0.04
(standard error)	(0.03)	(0.04)	(0.41)	(0.05)
[marginal effect]	[0.01]	[0.01]	[1e-3]	[3e-3]
Controls	✓	✓	✓	✓
N	149,093	65,407	68,889	36,543
Employment rate	0.01	-0.01	0.04*	-0.04
(standard error)	(0.02)	(0.02)	(0.02)	(0.03)
[marginal effect]	[1e-3]	[-0.01]	[0.01]	[-4e-3]
Controls	✓	✓	✓	✓
N	149,093	65,407	68,889	36,543

Robust standard errors are reported in round brackets. The weight variable used is *ilgwt26*. For each individual, I only use the weight in the first year the respondent joined the panel. GDP, Unemployment and Employment are detrended using an HP filter. GDP is in billions.
* 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Table 3.6: Logit coefficients: PSE enrollment by ability type (father's education)

Dependent variable:	PSE enrolment		University enrollment		College enrolment	
	HIGH father's education ≥bachelor's degree	LOW father's education < bachelor's degree	HIGH father's education ≥ bachelor's degree	LOW father's education < bachelor's degree	HIGH father's education ≥ bachelor's degree	LOW father's education < bachelor's degree
GDP	0.01***	-1e-4	2.2e-3	-0.02***	0.02***	0.01***
	(4.8e-3)	(2.3e-3)	(5.9e-3)	(3.8e-3)	(7.5e-3)	(3.1e-3)
Controls	✓	✓	✓	✓	✓	✓
N	21,202	127,891	14,506	50,901	7,124	61,765
	HIGH father's education > high school	LOW father's education ≤ high school	HIGH father's education > high school	LOW father's education ≤ high school	HIGH father's education > high school	LOW father's education ≤ high school
GDP	8.6e-3***	-1.2e-3	-2e-3	-0.01***	0.02***	4.8e-3
	(3.3e-3)	(2.6e-3)	(4.8e-3)	(4.8e-3)	(4.8e-3)	(3.5e-3)
Controls	✓	✓	✓	✓	✓	✓
N	51,706	97,387	30,233	35,174	20,970	47,919

Each estimation includes the same variables as in Table 3.2. The stars indicate the significance level: * indicates 10-percent significance level , ** indicates 5-percent significance level, *** indicates 1-percent significance level.

Table 3.7: Logit coefficients for unemployment: PSE enrollment by ability type (father's education)

Dependent variable:	PSE enrolment		University enrollment		College enrolment	
	HIGH father's education $\geq$bachelor's degree	LOW father's education $<$ bachelor's degree	HIGH father's education $\geq$ bachelor's degree	LOW father's education $<$ bachelor's degree	HIGH father's education $\geq$ bachelor's degree	LOW father's education $<$ bachelor's degree
Unemployment rate	-0.15*	0.07**	-0.03	0.21***	-0.17	-0.03
	(0.08)	(0.03)	(0.09)	(0.05)	(0.13)	(0.04)
Controls	✓	✓	✓	✓	✓	✓
N	21,202	127,891	14,506	50,901	7,124	61,765
	HIGH father's education $>$ high school	LOW father's education $\leq$ high school	HIGH father's education $>$ high school	LOW father's education $\leq$ high school	HIGH father's education $>$ high school	LOW father's education $\leq$ high school
Unemployment rate	-0.03	0.09**	0.10	0.22***	-0.14**	0.01
	(0.05)	(0.03)	(0.06)	(0.06)	(0.07)	(0.05)
Controls	✓	✓	✓	✓	✓	✓
N	51,706	97,387	30,233	35,174	20,970	47,919

Each estimation includes the same variables as in Table 3.2. The stars indicate the significance level: * indicates 10-percent significance level , ** indicates 5-percent significance level, *** indicates 1-percent significance level.

Table 3.8: Logit coefficients: PSE enrollment by ability type (mother's education)

Dependent variable:	PSE enrolment		University enrollment		College enrolment	
	HIGH mother's education ≥bachelor's degree	LOW mother's education < bachelor's degree	HIGH mother's education ≥ bachelor's degree	LOW mother's education < bachelor's degree	HIGH mother's education ≥ bachelor's degree	LOW mother's education < bachelor's degree
GDP	0.01**	-1.3e-3	3.2e-4	-0.01**	0.02***	0.01**
	(5.4e-3)	(2.2e-3)	(6.7e-3)	(3.7e-3)	(8.0e-3)	(3.0e-3)
Controls	✓	✓	✓	✓	✓	✓
N	16,698	132,395	11,590	53,817	5,902	62,987
	HIGH mother's education > high school	LOW mother's education ≤ high school	HIGH mother's education > high school	LOW mother's education ≤ high school	HIGH mother's education > high school	LOW mother's education ≤ high school
GDP	0.01**	-1.1e-3	1.0e-3	-0.01***	0.02***	0.01*
	(3.4e-3)	(2.6e-3)	(4.5e-3)	(4.7e-3)	(4.9e-3)	(3.5e-3)
Controls	✓	✓	✓	✓	✓	✓
N	52,231	96,862	30,631	34,776	21,305	47,584

Each estimation includes the same variables as in Table 3.2. The stars indicate the significance level: * indicates 10-percent significance level , ** indicates 5-percent significance level, *** indicates 1-percent significance level.

Table 3.9: Logit coefficients for unemployment: PSE enrollment by ability type (mother’s education)

Dependent variable:	PSE enrolment		University enrollment		College enrolment	
	HIGH mother’s education ≥bachelor’s degree	LOW mother’s education < bachelor’s degree	HIGH mother’s education ≥ bachelor’s degree	LOW mother’s education < bachelor’s degree	HIGH mother’s education ≥ bachelor’s degree	LOW mother’s education < bachelor’s degree
Unemployment rate	-0.13	0.06**	-0.02	0.19***	-0.06	-0.03
	(0.09)	(0.03)	(0.11)	(0.05)	(0.14)	(0.04)
Controls	✓	✓	✓	✓	✓	✓
N	16,698	132,395	11,590	53,817	5,902	62,987
	HIGH mother’s education > high school	LOW mother’s education ≤ high school	HIGH mother’s education > high school	LOW mother’s education ≤ high school	HIGH mother’s education > high school	LOW mother’s education ≤ high school
Unemployment rate	0.01	0.06*	0.10	0.19***	-0.10	0.09
	(0.05)	(0.03)	(0.07)	(0.06)	(0.07)	(0.11)
Controls	✓	✓	✓	✓	✓	✓
N	52,231	96,862	30,631	34,776	21,305	47,584

Each estimation includes the same variables as in Table 3.2. The stars indicate the significance level: * indicates 10-percent significance level , ** indicates 5-percent significance level, *** indicates 1-percent significance level.

Table 3.10: Logit coefficients: Employment-to-PSE transition

Dependent variable:	Return to university	Return to college	Return to trades
GDP	0.02*	-4.2e-3	1e-3
	(1.2e-2)	(8.3e-3)	(0.01)
Controls	✓	✓	✓
Unemployment rate	-0.14	-0.21**	0.01
	(0.14)	(0.10)	(0.12)
Controls	✓	✓	✓
Employment rate	0.13	0.18***	0.01
	(0.08)	(0.06)	(0.07)
Controls	✓	✓	✓
N	4,937	7,788	6,421

Each estimation includes the same variables as in Table 3.2.

* 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Table 3.11: University enrolment by major

Dependent variable:	University enrollment in GROUP 1 (humanities/social sciences)	University enrollment in GROUP 2 (business)	University enrollment in GROUP 3 (science/math)
GDP	-0.01	0.01	-0.02**
	(6.4e-3)	(0.01)	(8.8e-3)
Controls	✓	✓	✓
N	16,874	8,009	7,008
	University enrollment in GROUP 4 (agriculture)	University enrollment in GROUP 5 (health/fitness)	University enrollment in GROUP 6 (other)
GDP	-0.06**	0.01	0.05**
	(0.02)	(0.01)	(0.02)
Controls	✓	✓	✓
N	972	5,351	1,081

Each estimation includes the same variables as in Table 3.2.

* 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Table 3.12: Logit coefficients: University enrollment by degree

Dependent variable:	First-degree enrollment (=1 if enrolled and this is the first university degree, =0 if not enrolled)	Advanced-degree enrollment (=1 if enrolled and already has bachelor's degree, =0 if not enrolled)
GDP	-0.01**	-3.6e-3
	(3.7e-3)	(5.8e-3)
Controls	✓	✓
Unemployment rate	0.20***	0.04
	(0.05)	(0.08)
Controls	✓	✓
Employment rate	-0.02	0.05
	(0.03)	(0.05)
Controls	✓	✓
N	42,287	39,136

Each estimation includes the same variables as in Table 3.2.
* 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Note that the number of observations indicates the number of groups (i.e. individuals) used in each regression. Some observations are dropped because there is no within-group variation in terms of the dependent variable.

Table 3.13: Decision to drop out of university

Dependent variable:	Drop =1 if dropped from university in ref. year =0 if did not drop						
GDP_T	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GDP_{T-1}	-	2.4e-4	2.6e-4	-	-	-	-
		(0.01)	(0.01)				
GDP_{T-2}	-	-	0.01	-	-	-	-
			(0.02)				
$GDP_T - GDP_{T-1}$	-	-	-	-3.6e-3	-1.7e-3	-1.1e-3	-9.8e-3
				(7.1e-3)	(8.0e-3)	(8.6e-3)	(9.3e-3)
$GDP_{T-1} - GDP_{T-2}$	-	-	-	-	7.4e-3	6.5e-3	1.7e-4
					(0.01)	(0.01)	(0.02)
$GDP_{T-2} - GDP_{T-3}$	-	-	-	-	-	6.5e-3	0.01
						(0.01)	(0.02)
$GDP_{T-3} - GDP_{T-4}$	-	-	-	-	-	-	0.02
							(0.02)
Observations	6,913	6,913	6,913	6,913	6,913	6,913	6,913

The estimation includes the same variables as in Table 3.2. * 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Table 3.14: Impact of economic conditions in previous years

Dependent variable:	University enrollment				College enrollment			
GDP_T	-0.01*	-0.01**	-	-	0.01***	0.01***	-	-
	(3.3e-3)	(3.4e-3)			(2.9e-3)	(2.9e-3)		
GDP_{T-1}	2.3e-3	2.2e-3	-	-	3.8e-3	3.7e-3	-	-
	(2.7e-3)	(2.8e-3)			(2.5e-3)	(2.6e-3)		
GDP_{T-2}	-	-2.6e-3	-	-	-	-5.4e-3	-	-
		(3.8e-3)				(3.5e-3)		
$Unemployment_T$	-	-	0.16***	0.16***	-	-	-0.04	-0.04
			(0.04)	(0.04)			(0.04)	(0.04)
$Unemployment_{T-1}$	-	-	-1e-3	-3e-3	-	-	0.01	0.01
			(0.03)	(0.03)			(0.03)	(0.03)
$Unemployment_{T-2}$	-	-	-	0.05	-	-	-	-0.03
				(0.04)				(0.03)
N	65,407	65,407	65,407	65,407	68,889	68,889	68,889	68,889

The estimation includes the same variables as in Table 3.2. * 10-percent significance level , ** 5-percent significance level, *** 1-percent significance level.

Figure 3.1: Deviation from HP trend of GDP and PSE enrollment

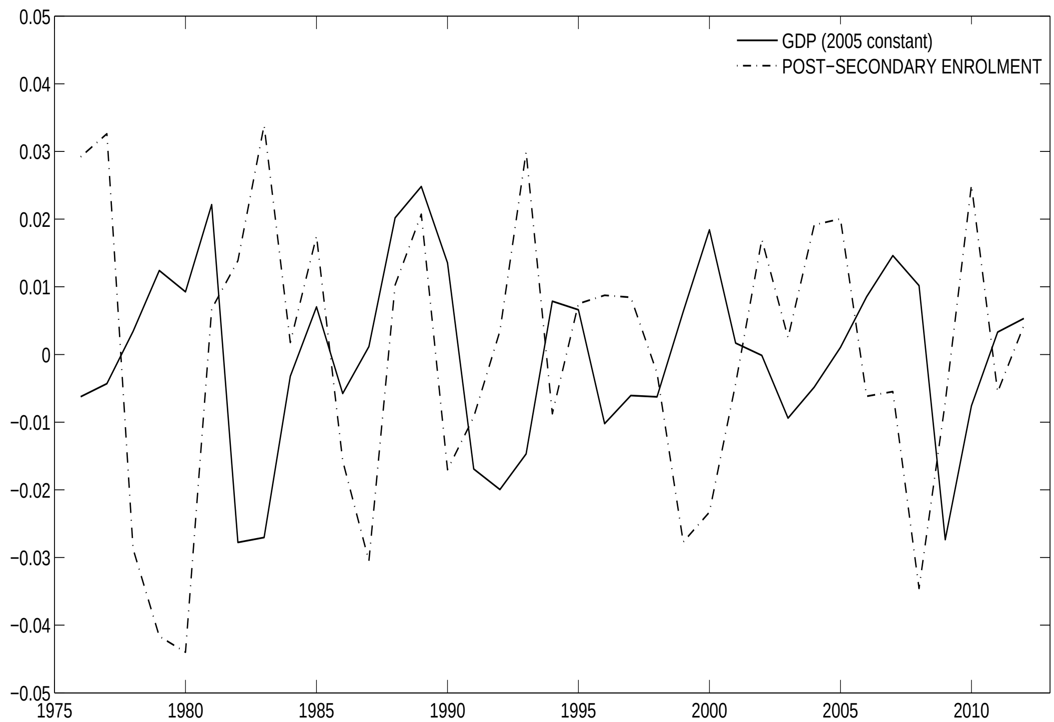
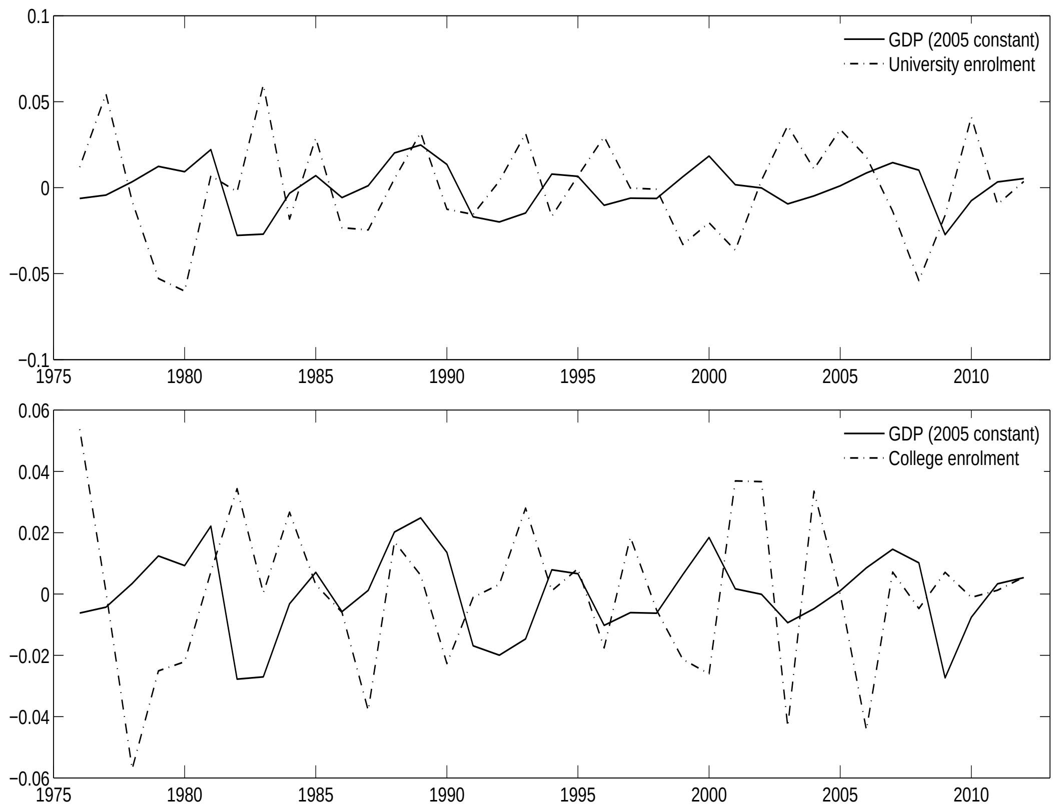


Figure 3.2: Deviation from HP trend of GDP, university and college enrollment



Conclusions

This thesis has investigated the effect of business cycles on individuals' decisions, especially regarding education and labor supply. From a theoretical perspective, economic downturns stimulate enrollment in post-secondary education by reducing the opportunity cost of education (i.e. the forgone labor income), suggesting that education and human capital accumulation should be counter-cyclical. This hypothesis is consistent with the fact that post-secondary educational institutions in North America experienced a boom in enrollment rates during the recent financial crisis. However, the literature provides inconsistent empirical results. My dissertation has confirmed both theoretically and empirically that, on average, individuals accumulate more skills and knowledge during economic crises. However, there are important differences at the individual level, which have been ignored in the literature.

The first chapter has shown that low-productivity individuals take advantage of the education sector during a recession by substituting schooling for work and accumulating more human capital. Whereas, high-productivity individuals earn a higher labor income and face a higher opportunity cost of education. Therefore, they are less likely to leave the labor market to accumulate more human capital. These results are confirmed empirically using survey data from the Current Population Survey (1986-2011). A one-percent increase in GDP above trend decreases the likelihood of being enrolled in college by 1.37 percentage points. The impact is stronger on low-productivity individuals compared to the rest of the population.

These findings have implications on the volatility puzzle in RBC models. The second chapter has shown that it is possible to improve the ability of the model to predict labor supply volatility by modeling heterogeneity in productivity. Since the cost of reducing hours worked is lower for low-productivity individuals, hours worked fluctuate more for them compared to the rest of the population. Therefore, it is possible to increase aggregate labor supply volatility by introducing heterogeneity in productivity into the model. In fact, a model without productivity differences among agents can explain 42% of the labor supply volatility in the data. The percentage increases to 60% when heterogeneity among agents (in terms of learning productivity) is included in the model. This result suggests that productivity differences, previously ignored in the literature, are as important as home production in order to explain the empirical volatility of hours worked in life-cycle RBC models. Further, previous papers in the literature show that education can explain the volatility puzzle in a representative-agent setting. I have shown that this is no longer the case once heterogeneity is introduced in the model and agents face a finite lifetime.

Finally, the third chapter has investigated the empirical relationship between business cycles and PSE decisions by using Canadian data. The cyclicality of schooling decisions has been extensively analyzed in the literature by using US data. However, there are no studies on the Canadian economy. Further, the analysis in the third chapter is based on longitudinal data from the Survey of Labour and Income Dynamics (1993-2010), while previous papers in the literature focused on pooled cross-sectional data. Panel data allow to follow individuals over time and investigate students decisions after enrollment. Main results have shown that university enrollment is counter-cyclical. The counter-cyclicality is stronger for low-ability individuals, compared to the rest of the population. This finding is consistent with the results in the first chapter. Contrary to university enrollment, college enrollment is pro-cyclical and enrollment in other (non-university) PSE institutions is acyclical. This result suggests that economic downturns stimulate the acquisition of theoretical rather than practical education. Finally, macroeconomic conditions mainly affect decisions of recent high-school graduates, whereas the impact on non-recent graduates is weak.

In summary, this dissertation has shown that heterogeneity among agents matters both theoretically and empirically. Individuals react differently to macroeconomic conditions by adjusting their education and labor market decisions. Taking into account these differences is very important in order to explain both labor supply volatility in RBC models and the cyclicality of PSE enrollment.

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