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Essays on saving for child's college

A Dissertation Presented

by

Junyi Zhu

to

The Graduate School

in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy

in

Economics

Stony Brook University

May 2010

Stony Brook University

The Graduate School

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Abstract of the Dissertation

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2010

How effective tax-favored education saving accounts (ESA) can foster the incentive of saving for child's college among heterogeneous families is still a debate. My dissertation contributes to this query by analyzing the main uncertainty of college saving - child's ability - in the context of the saving with learning model and an empirical examination of the effectiveness of ESA. This dissertation can be divided into three chapters.

The first chapter develops a dynamic model combining asset accumulation and learning to explain the parents' forward-looking saving behavior when they are confronted with a real option of college choice due to uncertainty of the child's ability. The model infers, with enough time spent learning, that information can improve parents' welfare. This can be accomplished by better allocating the consumption to accommodate the burden of college cost given both asset status and child's true ability.

Then, I test the implications of the model from Panel Study of Income Dynamics/Child Development Supplement & Transition into

Adulthood (PSID/CDS & TA) (1997-2005) in the second chapter. This empirical study investigates college saving behavior when learning is present. Data suggest pessimistic and/or rich parents might reduce the college saving, which confirms the interaction of wealth and learning effects predicted by this model. The result also supports the state dependence of parents' college expectation and diminishing persistence over time due to learning.

The third chapter is devoted to a policy study on education saving accounts (ESAs). I examine whether the contribution to ESA is associated with education saving propensity (ESP) among families with different income by using Survey of Consumer Finance (1998-2007). The model is estimated by a dynamic synthetic panel. The evidence suggests that only the poor families significantly utilize ESAs to fulfill ESP. Relatively richer families might mainly treat ESA as a tax shelter. I then provide the justification on the ineffectiveness of ESA by using my theoretical model. A number of fiscal policy improvements are proposed to encourage early learning child's ability in an effort to raise the economic efficiency of ESA.

To my parents and sister.

Contents

List of Figures	viii
List of Tables	ix
Acknowledgements	x
1 Introduction	1
2 Asset accumulation with learning: a theoretical model of college saving	4
2.1 Introduction	4
2.2 Literature	5
2.3 Model	7
2.3.1 Main model	7
2.3.2 Two contrast models	12
2.3.3 Wealth effect	13
2.3.4 Learning effect	15
2.4 Solutions	16
2.4.1 Characterization of policy rules	17
2.4.2 Evolution of policy rules	18
2.4.3 Wealth effect on college saving	19
2.4.4 Implications of learning in college saving	19
2.4.5 Goodness of fit	20
2.5 Conclusion	22
3 Empirical evidence on the college saving with learning	28
3.1 Introduction	28
3.2 Data	29
3.3 Specification and empirical issues	31
3.3.1 Test on college-bound choice	31
3.3.2 Test on college saving level	34

3.4	Results	36
3.4.1	College-bound choice	36
3.4.2	College saving	38
3.5	Conclusion	40
4	Education saving propensity and education saving accounts	47
4.1	Introduction	47
4.2	Data	51
4.3	Estimation strategy	54
4.4	Empirical model	55
4.4.1	Specification	55
4.4.2	Estimation method	57
4.5	Results	58
4.6	Policy implication	60
4.6.1	Inefficiency of tax-preferred ESA to encourage ESP	61
4.6.2	Policy suggestion	61
4.7	Conclusion	63
5	Summary	66
	Bibliography	68
	Appendix A Data description	75
A.1	Variables from NELS88	75
A.2	Variables from PSID/CDS & TA	76
A.2.1	Asset/income	76
A.2.2	Signal of child's cognitive ability	77
A.2.3	College expectation/outcome	78
A.2.4	Others from PSID/CDS & TA	78
A.2.5	Yearly college expenditure from NCES	79
	Appendix B Numerical algorithm	80

List of Figures

1.1	Skewness of the raw distribution	2
2.1	Asset next period in the white-collar state	23
2.2	Evolution of ability thresholds	24
2.3	Education saving next period in the white-collar state	25
2.4	Evolutions of policy rule - college savings	26
2.5	Evolutions of policy rule - ability threshold	27
4.1	Income of households with ESA and ESP	49

List of Tables

2.1	Baseline parameters used in the exercises for Figure 2.1, 2.2, 2.3, 2.4 and 2.5	17
2.2	Calibrated parameters for the replication experiment	20
2.3	Dynamics of college-bound choices	21
3.1	Summary statistics of PSID/CDS & TA (1997-2005)	41
3.2	Estimated effects of state dependence, wealth and learning on college expectation/outcome - I. Asset regressor excludes housing	43
3.3	Estimated effects of state dependence, wealth and learning on college expectation/outcome - II. Asset regressor includes housing	44
3.4	Alternative specifications: existence of state dependence and convergence of wealth effect on college expectation/outcome	45
3.5	Estimated effects of wealth and belief on college saving	46
4.1	Characteristics of households with child by the ownership of ESAs and ESPs, 2001-2007	64
4.2	GMM estimate for the association between ESP and the contribution to ESA	65

Acknowledgements

I am indebted to the helpful advices and encouragements from Sílvio Rendon, Hugo Benítez-Silva, Warren Sanderson and Mark Montgomery. I also thank Michael Zweig for providing me the access to the computational facility in Center for Study of Working Class Life, Stony Brook University. Thomas Muench shared with me his knowledge of optimization. Pradeep Dubey expressed his interest in my work and his viewpoint in the topic of education saving. Boyan Jovanovic provided many useful references, possible extensions and friendly encouragement. Many thanks are due to all my colleagues and Wei Tan in Applied Microeconomics Workshop at Stony Brook who offered me with valuable suggestions.

Of course, I am grateful to my parents and sister for their patience and *love*. Without them this work would never have come into existence (literally).

Chapter 1

Introduction

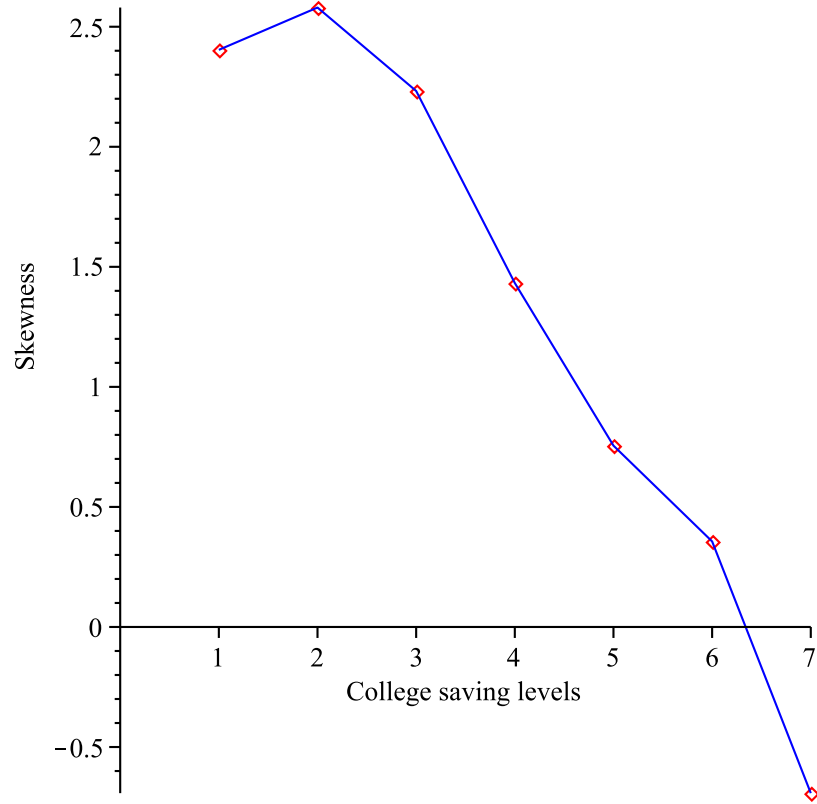
When altruistic parents consider the financial preparation for child's future higher education, they are confronted with the tradeoff between consumption smoothing and college premium. There are uncertainties involved with magnitude of and access to this premium: mainly, parents might only have a noisy inference on child's ability which is the key determinant of college premium.¹ However, college tuition (plus room, board and other costs) is expensive in US and thus it takes time for parents to financially well prepare for it before college age.² There might be redundant saving for tuition if child could not go to college or insufficient saving for tuition if child can be eligible for college.³ Either case will cause welfare loss in terms of either sacrifice of consumption in earlier period or slip of chance to improve child's career return. To reduce these risks, naturally, parents can utilize the observation from child's miscellaneous performances to well gauge her ability and thus decrease the uncertainty on it. I adopt this angle to develop the model by linking consumption smoothing and learning in an effort to explain several empirical characteristics on college saving and provide insights for policy related with college saving.

Figure 1.1 reveals the skewness of an empirical distribution, probability (college saving level when child is at 12th grade | college saving level at 8th grade), with respect to college saving level at 8th grade from National Education Longitudinal Study of 1988 (NELS88):

¹Ability has impacts on the premium such as suitability with college education and precollege academic/non-academic performances, which are important factors involved with the possibility and quality of college admission.

²I assume it is at the age of 18 for everyone which is true for the majority in US. Earlier college enrollment is excluded.

³Throughout the dissertation, parents are assumed to make child's college-bound choice by cost-benefit analysis. This leads to an *ex post* eligibility which means child's college premium decided by her revealed ability is worth the college cost.



Source: NELS88 (see Appendix A.1 for details on college saving questions from this survey). The college saving level is an ordered variable represented by the tickmarks in the horizontal axis. The range represented are:

8th grade (\$) - **1**: none, **2**: <1,000, **3**: 1,001-3,000, **4**: 3,001-6,000, **5**: 6,001-10,000, **6**: 10,001-15,000, **7**: >15,000;

12th grade (\$) - **1**: none, **2**: <1,000, **3**: 1,001-5,000, **4**: 5,001-10,000, **5**: 10,001-15,000, **6**: 15,001-30,000, **7**: >30,000.

Figure 1.1: Skewness of the raw distribution: probability (college saving level when child is at 12th grade) condition on college saving level at 8th grade

There is a striking evidence that skewness is decreasing with initial education saving level. The rule of Bayesian learning can provide an unsurprising interpretation: parents with prior lower than the child's true ability are not confident enough to save much at 8th grade. But they would have more chance to boost than suppress their beliefs because they are more likely to receive signals better than their priors. The same line of logic can deduce that parents with prior higher than the true one would achieve the opposite state. The naturally positive relationship between belief and college saving can produce this observation.

Building on this insight, Chapter 2 introduces both learning and wealth effects on the investment over risky asset (college saving) in search with saving model.⁴ The simulated outcome from a calibrated model can well replicate the feature of decreasing skewness shown in Figure 1.1. Value of learning, though under full self-enforcement and availability of information in my model, can be restricted only by physical constraint, which is different from other typical learning model where only unwillingness or inaccessibility can distort information acquisition.

The empirical study in Chapter 3 by using Income Dynamics/Child Development Supplement & Transition into Adulthood (PSID/CDS & TA) (1997-2005) test important predictions from the theoretical model. This is the first investigation on the existence of learning behavior and its interaction with wealth in the context of college saving. The estimated holding of college saving is around \$1,200 during 1997-2005 for a family with average child and zero total net wealth in the sample.

Finally, Chapter 4 evaluates the economic efficiency of education saving accounts (ESAs). Since there is no real public panel data available to address ESA, the empirical model is established on an age-specific pseudo panel from Survey of Consumer Finance (SCF; 1998-2007). 'System GMM' estimator shows only low income household open ESA significantly in the interest of education reasons. There is evidence of abusing ESA for other purposes.

⁴Miao and Wang (2006) proposes a similar framework with the notion of real option instead of search. But their concentration about wealth effect is on the survival rate of entrepreneur investment.

Chapter 2

Asset accumulation with learning: a theoretical model of college saving

2.1 Introduction

I construct a finite-horizon saving model with saving decision depending on asset level and belief on child's ability over time. In the last period, parents decide whether to send child to college conditional on their wealth status and child's revealed true ability level, which creates an option value. By observing child's performance each period, parents use Bayesian rule to update their belief and direct their saving strategy by choosing either orienting towards an additional constant tuition cost or not. This model is among the first efforts to incorporate learning into search with saving model. The calibration result does fit the empirical dynamics of college-bound expectation.

The main implications from the college saving model with learning unfolded in this chapter are:

- Optimistic parents tend to save more in terms of total asset and extra contribution towards tuition cost.
- Richer and/or optimistic parents set more lenient standard in terms of child's performance when making college-bound saving decision .

- There might be disincentive to invest in college saving as parents become richer.
- Given enough time of learning, information can improve parents' welfare by inducing the poorer and/or pessimistic parents to start college saving earlier for their children who deserve and helping richer and/or optimistic parents to reduce the unnecessary college saving for their children who deserve not so much or at all.¹

Section 2.2 summarizes the related literatures. Section 2.3 presents model setup and implications. Section 2.4 illustrates the policy rules, the contribution of learning in this model and a replication test by using simulation from a calibrated model. Section 2.5 reviews this theoretical model.

2.2 Literature

This chapter draws the ideas from the research on saving with search and search with learning. The reliance of optimal stopping rule about ability belief on wealth level creates the dynamic interaction between saving and learning behavior in my model, which is not present in the rest of search models.² The study on saving with search appears in Danforth (1979), Rendon (2006) and Hansen and İmrohorođlu (1992). Danforth (1979) and Rendon (2006) shows the property that the richer the worker is the more selective he is so that his reserved wage is higher. Similarly, my model claims that richer parents are more lenient so that their lowest belief standard on child's ability declines. Jovanovic (1979) is a seminal contribution on how decision maker searches the best offer with uncertainty while learning his return ability which determines

¹Simply speaking, parents' intertemporal consumption-saving choice is closer to the optimal state when uncertainty of child's ability disappears.

²The parents have to seek the optimal stopping rule on the belief updated each period to determine if they should stay and save in the riskier but better paid saving state towards college or a non-college-bound state with predetermined saving strategy but less payoff.

his offer. It explains the evolution of policy rules by a dynamic search model with learning and uses them to interpret features of labor market data.

My model contributes to the real option literature by introducing learning, wealth effect and their joint impact on option value altogether. Few studies have incorporated learning and intertemporal consumption-saving motive into real option model. [Miao and Wang \(2006, 2007\)](#) introduced precautionary saving motive and learning into entrepreneur's investment decision regarding real option.³ Volatility can increase both the option and learning values, which might, however, be offsetted by precautionary saving motive. [Campañale \(2004\)](#) also used a consumption-saving model with learning to suggest values from learning and option of exiting self-employment can explain why agent might stay as entrepreneur even if return is below the one on the stock upon entry. Many papers have devoted to the application of real option model in human capital investment. [Heckman et al. \(2006\)](#) show both theoretically and empirically the existence of sequential option of schooling choice and uncertainty of child's future return can account for the downward bias in static Mincer equation estimation.⁴ [Hogan and Walker \(2007\)](#) and [Jacobs \(2007\)](#) applied real option theory in human capital investment to discuss timing of college/working choice.

There have been many literatures exploring the interrelationship between consumption smoothing and college investment or intra-family interaction due to learning. But these studies do not connect financial preparation with learning, which is emphasized in my model. [Keane and Wolpin \(2001\)](#) and [Morris \(2003\)](#) built and estimated the parents' consumption-saving model when preparing for child's college financially with her future return uncertainty. [Cudmore \(2005\)](#) develops a theoretical model where parents make investments in the human capital of their children and save for post secondary education expenses. This model captures the fact that the potential opt-out penalty will reinforce the incentive to invest in child's earlier human capital when college saving accounts have been chosen.⁵ The learning of child's ability is heavily documented in the psychological literature on the parent-child relationships and children development ([Maccoby and Martin 1983](#); [Osofsky and Connors 1979](#)). [Akabayashi \(2006\)](#) proposes a dynamic model of child's human capital development with the introduction of endogenous time preference ([Becker and](#)

³[Dixit et al. \(1994\)](#) pioneer the concept of real option.

⁴The others include [Belzil and Hansen \(2002\)](#); [Cunha et al. \(2005\)](#); [Keane and Wolpin \(2001\)](#) and [Heckman and Navarro \(2007\)](#).

⁵This chapter shares the same intuition by showing there is motive to avoid loss in terms of consumption smoothing due to insufficient saving as long as parents have made contributions in college saving previously. This is actually self-enforcing so that the presence of college-saving accounts is not required.

Mulligan 1997) and imperfect monitoring on the basis of parent-child behavioral interaction. The author analyzes the impact of belief differences on how parents learn the child's potential. The solutions are used to disentangle the causes of maltreatment.

2.3 Model

Above all, I present the main model of saving with multi-period learning, which bears a mixture of impacts from wealth and learning on policy rules. To disentangle the wealth and learning effects, particularly due to the presence of option value in college-bound choice each period, I will then introduce one auxiliary model without uncertainty and the other with uncertainty and one-period learning.⁶ The model implications are then drawn from the contrast study between main model and the others.

2.3.1 Main model

Belief updating

Consider a college saving model with $T + 2$ periods. Child is born at the beginning of period 0 with ability parameter θ and parents are endowed with a prior of θ : μ .⁷ The true θ is not revealed until the beginning of the $(T + 1)$ th period. At the beginning of each period from 0 to T , parents observe a noisy observation $y_t = \theta + u_t$, such as academic performance, where u_t is the random noise. Then, they use y_t to infer the true θ by Bayesian rule. After the updated belief of ability m_t is estimated, parents incorporate it in making choice regarding extra saving for child's college tuition besides the motive to smooth consumption. At the end of period $T + 1$, altruistic parents retire

⁶The former does not have either wealth or learning effects and the latter has almost only the wealth effect. They are actually the simplified versions of main model constructed for illustrative purpose.

⁷The belief on child's ability is interpreted as confidence level of parents in this study.

and determine if their child will be sent to college given the asset accumulated and the true ability revealed.⁸ The tradeoff lies between a constant tuition cost C and the child's discounted college premium between white-collar and blue-collar careers. The return from child's career, as viewed by parents, is simply defined as a multiplicity of one fixed factor and his ability parameter: college-educated child will become white-collar and receive $w\theta$ and child without college education will become blue-collar and receive $b\theta$, where $w > b > 0$ (both w and b also contain the altruism parameter).⁹ Besides, parents receive an income stream $\{I_t\}$ from period 0 to $T + 1$.¹⁰

I assume that θ and u_t are independently distributed with $\theta \sim N(\mu, \sigma_0^2)$ and $u_t \sim N(0, \sigma_\mu^2)$.¹¹ For $t \geq 0$, define posterior at period t : $m_t = E(\theta|y^t)$, prior at period 0: $m_{-1} = \mu$, and variance $\Sigma_{t+1} = E(\theta - m_t)^2$. m_t and Σ_{t+1} can be computed via the Kalman filter:

$$m_t = (1 - K_t)m_{t-1} + K_t y_t \quad (2.1a)$$

$$K_t = \frac{\Sigma_t}{\Sigma_t + R} \quad (2.1b)$$

$$\Sigma_{t+1} = \frac{\Sigma_t R}{\Sigma_t + R}, \quad (2.1c)$$

where $R = \sigma_u^2$ and $\Sigma_0 = \sigma_0^2$ the unconditional variance of θ . The recursions can be initialized from $m_{-1} = \mu$ given Σ_0 . From the parents' *ex ante* perspective at $t = 0, \dots, T - 1$, by using all the information $y^t = y_0, \dots, y_t$, m_{t+1} is drawn from a normal distribution $F(\cdot|m_t, t)$ with mean m_t and variance $K_{t+1}\Sigma_{t+1}$. Similarly, at $t = T$, $m_{T+1} = \theta$ is drawn from a normal distribution $F(\cdot|m_T, T)$ with mean m_T and variance Σ_{T+1} .

⁸The assumption that the uncertainty of ability is resolved at the end of period $T + 1$ reflects the fact that offer decision from a range of colleges can actually reveal the true ability related with job market return. Namely, there is ability sorting across schools. Note I assume college premium is exogenously uniform across schools.

⁹The range for θ is the whole real line. Therefore, the more accurate interpretation for the career return is the deviation from a baseline constant. I use this specification to acknowledge that child might not fit college so that they can have a negative θ . Since the baseline constant return is unrelated with the solution, I simply ignore it.

¹⁰At the current stage, I introduce income mainly as a reference for calibrating other variables, such as asset and tuition. I can propose the income dynamics in the future development.

¹¹To introduce the learning process, I follow the description from Section 5.6.2 and 6.7 of [Ljungqvist and Sargent \(2004\)](#) and also use the recursive projection technique (the Kalman filter) from chapter 5 of this book.

Problem for the parents

At each period t , parents make decision about best asset level for next period A_{t+1} , based on the updated belief m_t and asset A_t . Same as initial prior m_{-1} , initial assets A_0 is endowed. There is a constant rate of return r for both saving and borrowing.¹² The discount factor is $\beta \in (0, 1)$. The problem for parents is described by a Bellman equation:

$$V_t(A_t, m_t) = U\left(A_t + I_t - \frac{A_{t+1}}{R}\right) + \beta V_{t+1}(A_t, m_t), \quad (2.2)$$

for $t = 0, \dots, T$. At period $T + 1$, given asset A_{T+1} , revealed ability parameter θ and income I_{T+1} , $V_{T+1}(A_{T+1}, \theta) = \max[V_{T+1}^w(A_{T+1}, \theta), V_{T+1}^b(A_{T+1}, \theta)]$, where $V_{T+1}^w(A_{T+1}, \theta)$ and $V_{T+1}^b(A_{T+1}, \theta)$ are defined as follows:

- White-collar state:

$$V_{T+1}^w(A_{T+1}, \theta) = U(A_{T+1} + I_{T+1} - C) + \beta w\theta. \quad (2.3)$$

Parents pay tuition C and send child to college to receive discounted altruistic payoff $\beta w\theta$ from the child's post-graduation job market earning as white-collar worker.¹³

- Blue-collar state:

$$V_{T+1}^b(A_{T+1}, \theta) = U(A_{T+1} + I_{T+1}) + \beta b\theta. \quad (2.4)$$

Parents do not send child to college and receive discounted altruistic payoff $\beta b\theta$ from the child's job market earning as blue-collar worker.¹⁴

Recursive formulation

Parents are all faced with a natural borrowing limit B_t , which means they can borrow up to the discounted value of their income streams ([Hakansson](#)

¹²I use $R = 1 + r$ for the rest of chapter.

¹³This is to admit that parents have to wait for one more period (until child's graduation) to harvest the return. A constant tuition cost C represents the fact there is always an entry cost for college no matter what level it is in US. The child's career return $w\theta$ can be viewed as a Mincer equation $\ln(\text{wage of child})$. By this interpretation, my specification is actually an intra-household utility.

¹⁴Actually, the discount factor β is unnecessary since blue-collar career can start immediately at the end of $T + 1$. I maintain it for consistency, which only requires a reinterpretation of b .

1970; Ljungqvist and Sargent 2004; Miller 1974). The existence of liquidity constraint for household is consistent with most previous research.¹⁵ Any borrowing constraint below B_t is redundant with a utility function satisfying Inada condition (Rendon 2006). To make white-collar state feasible at period $T + 1$, A_{T+1} chosen at period T must be larger than $B_T^C = C - I_{T+1}$. Consequently, there is a tuition budget constraint $B_t^C = -\sum_{s=t}^{T+1} \frac{I_s}{R^{s-t}} + \frac{C}{R^{T+1-t}}$ at $t = 0, \dots, T$. If A_t is below this constraint, parents cannot afford tuition finally even if they keep consuming nothing for all the time. Bearing this in mind, the value functions confronted by the parents at $t = 0, \dots, T$, can be divided into two:

- Blue-collar state:

$$V_t^b(A_t, m_t) = \max_{B_{t+1} \leq A_{t+1}} \left\{ U\left(A_t + I_t - \frac{A_{t+1}}{R}\right) + \beta \int V_{t+1}^b(A_{t+1}, m_{t+1}) dF(m_{t+1}|m_t, t) \right\}, \quad (2.5)$$

which represents a state when parents totally drop the college-bound expectation and maintain a typical finite horizon saving motive for consumption smoothing only. They certainly receive a blue-collar career return from the child though the magnitude is still uncertain. The best saving strategy is A_{t+1}^b , which depends on A_t only.

- White-collar state:

$$V_t^w(A_t, m_t) = \max_{B_{t+1}^C \leq A_{t+1}} \left\{ U\left(A_t + I_t - \frac{A_{t+1}}{R}\right) + \beta \int \max[V_{t+1}^b(A_{t+1}, m_{t+1}), V_{t+1}^w(A_{t+1}, m_{t+1})] dF(m_{t+1}|m_t, t) \right\}, \quad (2.6)$$

which represents a state when parents still hold college-bound expectation with extra saving prepared for the positive possibility to pay tuition. The best saving strategy is A_{t+1}^w , which depends on both A_t and m_t .

Both are defined backwardly from T to 0 and $V_{T+1}^b(A_{T+1}, m_{T+1})$ and $V_{T+1}^w(A_{T+1}, m_{T+1})$ are defined in (2.4) and (2.3) respectively. This is a dynamic programming (DP) problem with a finite horizon $T + 2$. At each period, there are two state variables asset A_t and updated belief m_t . Policy rule is A_{t+1} ,

¹⁵For instance, Keane and Wolpin (2001).

which is either A_{t+1}^w or A_{t+1}^b depending on the state chosen. At $t = 0, \dots, T+1$, given asset A_t , parents settle the tradeoff between values from two states by determining an ability threshold $\bar{m}_t(A_t) = \{m_t | V_t^w(A_t, m_t) = V_t^b(A_t, m_t)\}$. This is the lowest belief on ability for the white-collar state to be acceptable.

The optimal value function as well as ability threshold can be classified into three cases depending on A_t : (1) $V_t(A_t, m_t) = V_t^b(A_t, m_t)$ and $\bar{m}_t(A_t) = \infty$ if $A_t < B_t^C$, which means the blue-collar state is the only affordable one; (2) $V_t(A_t, m_t) = V_t^w(A_t, m_t)$ and $\bar{m}_t(A_t) = -\infty$ if $A_{t+1}^b(A_t) \geq B_{t+1}^C$, which means the white-collar state is always dominant;¹⁶ (3) $V_t(A_t, m_t) = \max[V_t^w(A_t, m_t), V_t^b(A_t, m_t)]$ and $\bar{m}_t(A_t) \in (-\infty, \infty)$ if $A_t \geq B_t^C$ and $A_{t+1}^b(A_t) < B_{t+1}^C$, which is between the cases (1) and (2) when both states might be chosen with positive possibility. Therefore, the blue-collar state is chosen by either very poor parents or averagely rich parents whose incentive to smooth consumption dominates. The white-collar state is picked by averagely rich parents and their optimism in investment on child's ability dominates or very rich parents.

Whether the impact of learning can play a role is determined by the state chosen. Parents choosing white-collar state might switch to blue-collar state later and end up with blue-collar career though those really staying in blue-collar state can not switch to white-collar due to tuition budget constraint.¹⁷ In this sense, white-collar state bears an option to exit to blue-collar state any time in the future. Parents might opt out of this white-collar state when they receive a shock bad enough about child's ability. Thus, the learning value towards this option still exists. On the other hand, blue-collar state represents a state that parents' willingness to learn child's ability disappears since this is an absorbing state.¹⁸ Consequently, the saving choice becomes regardless of the effect of belief m_t and all the new information from then on.

Throughout this chapter, I define *college saving* by subtracting the alternative blue-collar saving level out of their best choice among parents in the white-collar state: $A_{t+1}^w(A_t, m_t) - A_{t+1}^b(A_t)$, for $m_t \geq \bar{m}_t(A_t)$. This corresponds to the extra saving motive besides consumption smoothing borne by parents in preparation for child's college cost.

¹⁶This results from the fact that V_t^b is never better than V_t^w given this asset status by their definitions in (2.5) and (2.6).

¹⁷The empirical observation supports the disallowance of this switch: both NELS88 and PSID/CDS & TA shows very low frequency of this pattern of transition for each period (3% in NELS88 between two waves and averagely 6.2% among three waves in PSID/CDS & TA), which is far lower than the other three patterns of transitions for a binary college-bound choice. This pattern can be included by introducing income or preference shocks; however, the main model implications are unchanged.

¹⁸This lack of learning is forced by the budget constraint if $A_{t+1}^b(A_t, m_t) < B_{t+1}^C$.

2.3.2 Two contrast models

In these alternative models, parents' choices at period $T + 1$ is still same as those specified in equation (2.3) and (2.4). If parents know exactly true ability parameter θ at period 0, by dropping the uncertainty about θ , this is a model without effects of learning and option. Then this problem turns into two saving choices with everything same except endowment at period $T + 1$ and salvage values: a college-committed state receive less income in the last period due to tuition cost but higher salvage value from child's white-collar career return; but the other non-college-committed state (this is just blue-collar state with certain payoff from child) leads to a lower blue-collar career return though without tuition cost finally. An ability threshold $\bar{\theta}(A_0)$ depending on initial asset A_0 can be solved by equalizing the return differential and differences between two present discounted utilities of consumptions from both states. This is the lowest ability for parents to choose the white-collar state. Parents can then pick the better state and corresponding saving strategies and stick with them from period 0. There is no option value from period one on.

On the basis of the case without uncertainty, I then introduce the ability uncertainty with one-period learning. Parents evaluate the uncertainty always by the initial belief before they are confronted with the same choices as those specified in equation (2.3) and (2.4) at $t = T + 1$. The value functions become¹⁹

$$V_T^{OL}(A_T, m_{-1}) = \max_{B_{T+1} \leq A_{T+1}} \left\{ U(A_T + I_T - \frac{A_{T+1}}{R}) + \beta \int \max [V_{T+1}^b(A_{T+1}, \theta), V_{T+1}^w(A_{T+1}, \theta)] dF(\theta|m_{-1}) \right\} \quad (2.7)$$

at period T and

$$V_t^{OL}(A_t, m_{-1}) = \max_{B_{t+1} \leq A_{t+1}} \left\{ U(A_t + I_t - \frac{A_{t+1}}{R}) + \beta \int V_{t+1}^{OL}(A_{t+1}, m_{-1}) \right\} \quad (2.8)$$

at $t = 0, \dots, T - 1$, where θ is inferred from a normal distribution $F(\cdot|m_{-1})$ with initial prior m_{-1} as mean for all the time. The policy rules as well as blue and white collar states are defined in the same way as those of main model except the optimal stopping rule, which is on the initial prior always: $\bar{m}_{-1}(A_t) = \{m_{-1} | V_t^w(A_t, m_{-1}) = V_t^b(A_t, m_{-1})\}$.²⁰ Furthermore, The value

¹⁹For distinguishing purpose, I use superscript OL to denote model of one-period learning as below; and the main model is then labeled main model.

²⁰To avoid redundant notations, I only present below the value functions of blue and white collar states at period T.

function for the white-collar state at period T imbedded in equation (2.7) can be shown as

$$V_T^{OLw}(A_T, m_{-1}) = \max_{B_{T+1}^C \leq A_{T+1}} \left\{ \beta^2(w-b) \int_{\bar{\theta}(A_{T+1})}^{+\infty} F_c(\theta|m_{-1}) d\theta + V_T^{OLb}(A_{T+1}; A_T, m_{-1}) \right\}, \quad (2.9)$$

where $F_c(\cdot|m_{-1}) = 1 - F(\cdot|m_{-1})$, $V_T^{OLb}(A_{T+1}; A_T, m_{-1}) = U(A_T + I_T - \frac{A_{T+1}}{R}) + \beta V_{T+1}^b(A_{T+1}, m_{-1})$ and V_{T+1}^b is specified in equation (2.3), and $\bar{\theta}(A_{T+1}) = \frac{U(A_{T+1} + I_{T+1}) - U(A_{T+1} + I_{T+1} - C)}{\beta(w-b)}$, *i.e.* the ability threshold in the last period.²¹ The main model can be viewed as built from models without uncertainty and one-period learning by sequentially introducing option value and multi-period learning.

2.3.3 Wealth effect

In this and next subsections, I present the wealth and learning effects by mainly using one-period learning model due to its simplicity. Wealth effects discuss how one state variable asset is related with the policy rules and learning effect summarizes how the other state variable prior determines the policy rules by itself and together with asset. Note it is implicitly assumed the other state variable is fixed when all of the wealth effects and learning effects I & II are introduced below. Since one-period learning model also bears the option value which wealth effects are concerned with, all of the wealth effects are shared by main model. The first two learning effects are shared by both models and the last two are not, which will be unfolded in Section 2.3.4.

The second term in the value function (2.9) bears the usual saving motive to smooth consumption. The first term shows the motive of saving additionally for college. This actually represents the option value of the college choice structure in this model which does not exist in the model without uncertainty. The college saving defined in the end of Section 2.3.1 can be interpreted as the investment to this risky option value. Then, the first and second order derivatives of this term with respect to A_{T+1} are

$$- F_c(\bar{\theta})\bar{\theta}' \quad (2.10)$$

²¹ V_T^{OLb} is same as value function (2.5) of blue-collar state at T in the main model except that initial prior m_{-1} is instead used to infer θ .

and

$$f(\bar{\theta})(\bar{\theta}')^2 + F_c(\bar{\theta})(-\bar{\theta}''), \quad (2.11)$$

where $f(\bar{\theta}) = F'(\cdot|m_{-1})$, $\bar{\theta}' < 0$ and $\bar{\theta}'' > 0$ by the definition of $\bar{\theta}(A_{T+1})$ and property of CRRA utility function. The first order derivative catches the wealth effect on option, which is positive. A marginal increase on wealth may avoid the hazard of losing a lump-sum value, the total discounted college premium $\beta(w - b)\theta$, since richness relax further their ability threshold. These two factors interactively determines

- **Wealth Effect I:** *the richer parents allow a lower ability threshold in selecting acceptable child for white-collar state over time.*²²

The first term in (2.11), second order derivative of wealth effect on option value, produces the convexity so that we have

- **Wealth Effect II:** *there exists the incentive of “oversaving” meaning extra sacrifice of consumption smoothing to cover beyond fixed “entry cost” of tuition and this motive increases with asset.*

Likewise, parents carry on this additional saving motive for all the periods. This intuition is actually shared by the discussion of puzzles in private equity premium of entrepreneur and human capital investment where people extend the duration of self-employed or schooling with irreconcilable observed return (Campanale 2004; Hogan and Walker 2007; Jacobs 2007; Miao and Wang 2007). These literatures use the typical results of real option model to explain these behaviors: the agent can capture the upside gains by investing and limit the downside losses by simply waiting until the option is sufficiently “in the money”. But the perspective is different in my model which lies on the wealth effect instead: wealth can increase risk taking behavior, which has been proposed by Miao and Wang (2006) and Cressy (2000).

However, the second term in equation (2.11) reveals the other aspect of wealth effect on option which is not discussed in these literatures: the marginal return from the child’s ability realization already “in the money” (above threshold) is decreasing with wealth. This concavity of wealth effect on option value creates

- **Wealth Effect III:** *there exists the disincentive to increase the contribution for college cost as asset grows.,*

²²The optimal stopping rule is defined on the other state variable, m_t . This adds the other line of dynamics because the interaction of two state variables on the value function plays a significant role in determining the threshold.

The total wealth effect towards the college saving defined in Section 2.3.1 depends on which term in (2.11) dominates.²³

2.3.4 Learning effect

The learning effect has four folds. The more optimistic parents (with higher prior) will gain more in saving the child's chance to be sent to college, which can be reflected by the positive marginal effect of prior on (2.10):

- **Learning Effect I:** *optimism lowers the ability threshold.*

The second one is on the role of belief. It is straightforward to show that the motive to raise college saving is increasing with m_{-1} :

- **Learning Effect II:** *optimism boosts college saving.*

Both effects are also shared by the main model: ability threshold is lower and college saving in any period is increasing when prior m_t for any t is higher. The statement about college saving can be seen from its definition at the end of Section 2.3.1 where m_t has only positive impact on total saving in white-collar state $A_{t+1}^w(A_t, m_t)$ instead of blue-collar state saving $A_{t+1}^b(A_t)$.²⁴ The third one is drawn from the fact of the degeneration of belief distribution as learning evolves, which exists only in the main model. This means, with enough learning and $\theta > 0$, the ability threshold \bar{m}_t (including the final one $\bar{\theta}$) converges to m_t (including m_T), which leads to the dominance of the convexity of wealth effect as shown in the first term of equation (2.11) since $f(\bar{\theta})$ diverges and $F_c(\bar{\theta})$, $\bar{\theta}'$, and $\bar{\theta}''$, given A_{T+1} , are bounded.²⁵ The implication is that

²³In the case of one-period learning model, m_t in college saving defined in the end of Section 2.3.1 is replaced by m_{-1} for all the time.

Strictly speaking, we can make the statement that the stronger effect II must mean the positive relationship between wealth and college saving. And negative relationship between wealth and college saving must imply the dominance of effect III. Further statements about the sufficiency and necessity might not be true because they are also involved with wealth effect on consumption smoothing.

²⁴The positive relationship between m_t and $A_{t+1}^w(A_t, m_t)$ can be produced by the application of Topkis's theorem (Topkis 1978).

²⁵The mechanism is that the variance of prior is smaller over time and ability threshold concentrates around the mean of prior. Therefore, the cross-sectional ability threshold over different wealth level becomes flatter and converge around the true ability as learning evolves. The condition $\theta > 0$ can guarantee the convergence since $\bar{\theta} > 0$ certainly. This actually represents the fact that college premium is positive, which is true for almost every child in reality according to most literatures. The alternative approach to introduce this learning effect is to assume truncated belief distribution, which might complicate the updating rule without bringing in additional insight.

- **Learning Effect III:** *with enough learning and $\theta > 0$, the positive relationship between wealth and college saving dominates in the main model.*

This is not certain in the model with one-period learning only. The fourth one links learning with option structure. In the one-period learning model, the college-bound option is open only in the end. No one would choose to exit or enter white-collar state during in-between periods. Otherwise, they should have done so in the very beginning to avoid the cost on consumption smoothing because they can fully forecast this action in period zero given no new information appears before last period. However, the main model with multi-period learning provides the chance of entry or exit conditional on the quality of signal:

- **Learning Effect IV:** *with enough learning and $\theta > 0$, parents with high belief and/or asset reduce the degree of oversaving, and those with low belief and/or asset can be induced to start college saving which does not happen in an environment lack of learning.*

The reason is that they can defer more saving until enough good signals arrive or opt out of white-collar state given bad signal. The following sections will continue on these issues by showing numerical and empirical evidences.

2.4 Solutions

This problem does not attain an analytical solution due to non-convexity. Since this is a mixture of optimal stopping and optimal control problem, the behavior of value function turns to be highly unpredictable. Regular polynomial approximations on value function do not render satisfactory results. I discretize the continuous state spaces to solve it numerically (see Appendix B).²⁶ The utility specified is a constant relative risk aversion (CRRA) func-

²⁶An efficient global optimization routine combined with polynomial approximation is under consideration to enable the model to incorporate more complications.

tion $U(C) = C^{1-\rho}/(1-\rho)$, where ρ is the coefficient of risk aversion. All the distributions are approximated by the truncated normal distribution.

2.4.1 Characterization of policy rules

Figure 2.1, 2.2 and 2.3 present the interactive impacts of the initial prior and asset on the policy rules of the main model at period one as described in Section 2.3.1.²⁷ Table 2.1 reports the parameter values used. Interest rate R , discount factor β and risk aversion coefficient ρ are drawn from typical literatures. Tuition cost C is calculated approximately as a present value of four years' college expenditures with this amount each year equal to the median yearly college expenditure in 2005, \$10,112, considering a growth rate of 6% drawn from the real change between 1997 and 2005 as in my PSID/CDS & TA sample.²⁸ The income I_t is picked from our target subsample as a median value across waves, which is assumed to be constant in the current stage. And the rest are chosen ad hoc in a reasonable range.²⁹ I plot the policy rules across one state variable while fixing the other one in two contrasting levels. Figure 2.1(a) shows that saving rises with wealth level in the white-collar state. This is driven by the typical incentive to smooth consumption. Figure 2.1(b) illustrates that saving is also an increasing function of prior m_{-1} , which is driven by the *Learning Effect II*. As discussed above, parents with better belief hold stronger motive to save furthermore to secure their college saving. The interactive effect of asset and prior on saving is also positive as shown in both figures.

Table 2.1: Baseline parameters used in the exercises for Figure 2.1, 2.2, 2.3, 2.4 and 2.5

Parameter	R	β	w	b	C	ρ	σ_u	σ_0	θ	I_t
Baseline value	1.015	0.98	4	1	4.3\15.3 ^{ab}	1.4	2	2	2	5.5 ^{bc}

^a C is \$43,000 in the exercise for Figure 2.1, 2.2 and 2.3 and \$153,000 for Figures 2.4 and 2.5.

^b 1,000\$.

^c I_t is constant for $t = 0, \dots, T + 1$.

Figure 2.2(a) displays the ability threshold $\bar{m}_0(A_0)$ and expected threshold next period $E(\bar{m}_1(A_0, m_0 \geq \bar{m}_0(A_0)) | m_{-1})$ across different asset A_0 given two

²⁷For this exercise, I set $T = 1$.

²⁸See Appendix A.2.5. This growth rate matches commonly in the literatures describing tuition change during this period, e.g., Reyes (2007).

²⁹The selection of parameters is not the emphasis in this section which simply provides a showcase of policy rules. A calibration is presented in Section 2.4.5 shortly.

comparing prior m_{-1} . They are all decreasing in assets, which matches with wealth effect I. In addition, when the wealth reaches certain level, the threshold drops to minus infinity, or say, disappear.³⁰ Figure 2.2(b) depicts that ability threshold is non-increasing with prior m_1 when belief updating starts, namely, at $t > 0$. This corresponds to the **Learning Effect I**. Both figures suggests the positive interactive effect of asset and prior on ability threshold.

Figure 2.3(a) and 2.3(b) demonstrate the impact of asset A_0 and prior m_{-1} on the expected value of college saving $E(A_1^w(A_0, m_0 \geq \bar{m}_0(A_0)) - A_1^b(A_0)) | m_{-1}$. The college saving, as shown in Figure 2.3(a) seems to have a decreasing trend with asset A_0 when it is large enough. But this pattern is uncertain when asset level is small. This follows the discussion on the **Wealth Effect III and IV** about the ambiguity of wealth effect.³¹ Figure 2.3(b) has a similar outcome to that in Figure 2.1(b) and they are both driven by the **Learning Effect II**.

2.4.2 Evolution of policy rules

This section presents a contrast study between the main model and the auxiliary models defined in section 2.3.2 in order to extend the discussion of the wealth effect on college saving and the implication of learning as described in the **Learning Effect III and IV**.³²

Figure 2.4 and 2.5 illustrate how college savings and ability thresholds evolve overtime in both one-period learning and multi-period saving with learning model under different combinations of initial states. Figure 2.4(a) shows true ability $\theta = 2$ and its threshold $\bar{\theta}(A_0)$ at period 0 when true ability is known initially. This reveals that, under the setting of parameters in this exercise, it is best to stay in the white-collar state from the beginning and finally send child to college for parents with either high or low A_0 since their ability thresholds are below true ability.

³⁰They are rich enough so that a saving strategy in white-collar state must dominate because it always includes the best saving choice from blue-collar state in their choice set. See the discussion below equation (2.6).

³¹This outcome could result from the insufficiency of learning effect particularly when there is only two periods of learning in this numerical exercise.

³²The simulations in this section share the same parameters as the exercises in Section 2.4 (see Table 2.1) except tuition cost, which is \$153,000. This much higher figure is to create illustrative outcomes. In fact, the tuition and fees for ivy league schools in 2008-2009 can range from \$34,290 to \$37,526 (source: Integrated Postsecondary Education Data System (IPEDS)). Thus, this figure of \$153,000 can be considered as a present value of tuition and fees for ivy league schools by the same calculation proposed previously.

2.4.3 Wealth effect on college saving

Figure 2.4(b) demonstrates the evolution of college saving in the white-collar state with one-period learning and college-committed state without uncertainty. They all grow over time because the need to save for college gets more imminent as time approaches the final period. Parents with high initial prior oversave for all the time (*Wealth Effect II*): their college saving exceeds the level of annualized tuition trajectory in the college-committed state.³³ Parents with low initial prior but high initial asset also choose the white-collar state. But parents with low initial prior and low initial asset decide not to send child to college from the beginning.³⁴ Therefore, given this low prior, wealth is positively related with college saving. However, given higher prior, low asset parents prepare more in college saving,³⁵ which again shows the evidence of existence/dominance of the *Wealth Effect III*: concavity of marginal effect of wealth on option value of college choice.

Figure 2.4(c) reveals the evolution of college saving when multi-period learning is allowed. Now the positive relationship between wealth and college saving is consistent and strong across different priors. This supports the *Learning Effect III* that learning tends to reinforce convex wealth effect on option value. Section 3.4.2 will revisit the impact of learning on wealth effect using empirical results.

2.4.4 Implications of learning in college saving

The value of learning can be particularly characterized in the following two scenarios. Figure 2.4(b) shows, in the low prior case, even exposure to information at the last period does improve some parents' college-bound decision since it introduces the option value, which is worth more for parents with advantage in asset than those poorer given this low prior: richer ones are thus induced to save and bet for a good realization of θ .³⁶

Figure 2.4(c) illustrates exactly the scenario described by the *Learning*

³³The level of oversaving can be measured by integrating over time the distance between trajectory in college-committed state and the one interested.

³⁴See the caption below Figure 2.4(b) for the interpretation on this type of parents.

³⁵It is discernible only at initial periods from this figure. I examined this is not due to computational errors. There are more distinctive results among other parameter specifications. However, to maximize the visual effect jointly across all the figures, this group of parameters are chosen.

³⁶Imagine parents have to make college decision based on the same prior $m_{-1} = -1.1$ when no information will be available any time. Then the expected return differential between white-collar career and blue-collar career is negative from the beginning. Therefore, they would definitely not send child to college no matter what wealth level they have.

Effect IV. There is welfare improvement from introducing learning in the point views of either reducing oversaving behavior among parents optimistic with child’s scholastic capability or lifting college preparation rate among parents pessimistic with child’s scholastic capability consequently.

Besides, Figure 2.5(a) and 2.5(b) also confirms both the **Wealth Effect I** and **Learning Effect I** about their relationships with ability threshold in a dynamic context.

2.4.5 Goodness of fit

To assess the accuracy of this model in presenting the impact from learning, I further report an experiment in an effort to replicate the dynamics of college-bound choice. In 2002 an 2005, PSID/CDS & TA sample asks parents whether they expect the child to go to college. I construct the statistics about the transition of the expectation as well as the total fraction of college-goers in 2005. The model is then calibrated by targeting the fraction of college-goers. T is simply chosen to be two in this experiment.

Table 2.2: Calibrated parameters for the replication experiment

R	β	ρ	I_t	C^l	A_0^l	A_0^h
1.015	0.98	1.4	5.5 ^{a,b}	0 ^c	-6.37 ^{a,d}	3913.73 ^{a,d}
w	b	σ_u	σ_0	θ	m_{-1}^l	m_{-1}^h
4	1	1	2	1.83	-9.11	10.33

^a \$10,000.

^b I_t is constant for $t = 0, \dots, T + 1$.

^c This is drawn from an empirical distribution of national college cost available on Baum et al. (2005: page 3) (see Figure 1: Distribution of Full-Time Undergraduates at Four-Year Institutions by Published Tuition and Fee Charges, 2005-06 from this report). It ranges from \$3,000 to \$33,000 or so. I set this distribution to be only truncated at zero from below.

^d The 25%, 50% and 75% percentiles are \$9,555, \$50,414 and \$140,413.

Table 2.2 display the parameter calibrated. Interest rate R , discount factor β and risk aversion coefficient ρ are chosen from the literature. Income I_t are selected from PSID/CDS & TA by the same approach in Section 2.4.1. This simulation is formed on a joint sampling over a uniform distribution of initial prior on $[m_{-1}^l, m_{-1}^h]$ and initial empirical asset distribution $[A_0^l, A_0^h]$ observed from the wave zero in the full sample used in the empirical study in Chapter

3.³⁷ The college cost C also follows an empirical distribution as described under Table 2.2. The rest of parameters are obtained by a trial and error procedure.

Table 2.3: Dynamics of college-bound choices

	Data	Model
Entry rate % (1st period)	47.2	51.3
Entry rate % (2nd period)	23.9	12.7
Exit rate % (1st period)	13.7	11.9
Exit rate % (2nd period)	19.7	28.5
Survival rate % (1st period)	86.3	92.3
Survival rate % (2nd period)	71.25	73.3
Fraction of college-goers %	66.3	68.8

¹ First period corresponds to 2002 in data and $t = 1$ in model. Second period represents 2005 in data and $t = 2$ in model.

² Entry rate: $\Pr(\text{parents have college-bound expectation/enter the white-collar state at } t \mid \text{they do not have expectation/do not stay in the white-collar state at } t - 1)$.

³ Exit rate: $\Pr(\text{parents do not have college-bound expectation/leave the white-collar state at } t \mid \text{they do have expectation/do stay in the white-collar state at } t - 1)$.

⁴ Survival rate: $\Pr(\text{parents still have college-bound expectation/stay in the white-collar state at } t \mid \text{they do have expectation/stay in the white-collar state at } t - 1)$.

⁵ This is the fraction in terms of the whole sample.

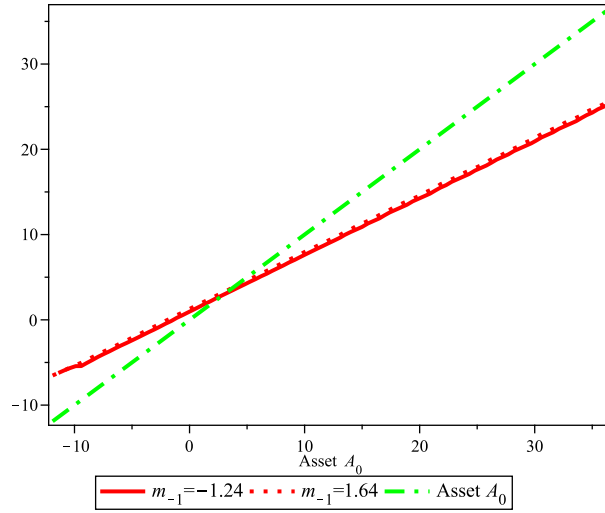
The results are compared in Table 2.3. It is not surprising that fraction of college-goers is matched very well since this is the calibration target. The general pattern of dynamics has been replicated: entry rate drops, exit rate increases and survival rates decreases. This implies the parents, by and large, overestimate the child’s ability initially. The calibrated initial prior interval confirms this in the sense that most section is higher than the true ability θ . The first period exit rate from my model is 11.9 percent, which is quite close to 13.7 percent in the data. The survival rate in the second period from mine is 73.3 percent, which is also not far away 71.25 percent in the data. The fact that the non-targeting statistics can approach the pattern and numbers in the reality shows the learning with saving model does shed the light on college-bound decisions reasonably.³⁸

³⁷See Section A.2.1 for details.

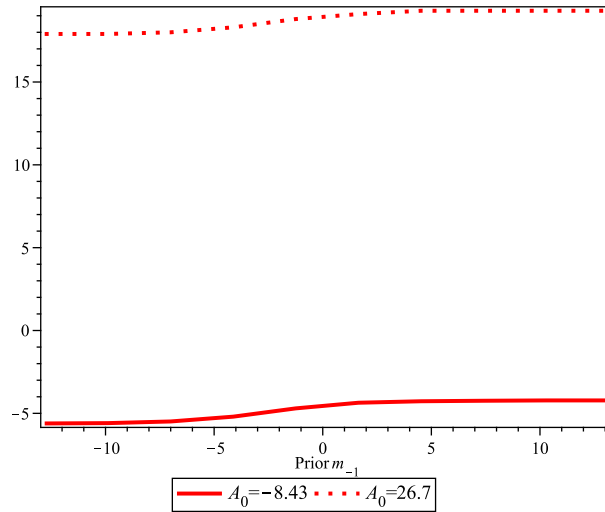
³⁸The degree of transition is much more outstanding in my model. The most straightforward reason is the learning period is too short as I set. On the other hand, to allow the correlation in the initial states might improve the fitting.

2.5 Conclusion

The saving model with learning in this chapter provides explanation for the important empirical features about college saving observed from NELS88: decreasing skewness of an empirical distribution, probability (college saving level when child is at 12th grade | college saving level at 8th grade), with respect to college saving level at 8th grade. Given enough time of learning, oversaving among optimistic parents or inability to save for college among pessimistic parents might be alleviated because the positive relationship between option value and learning.

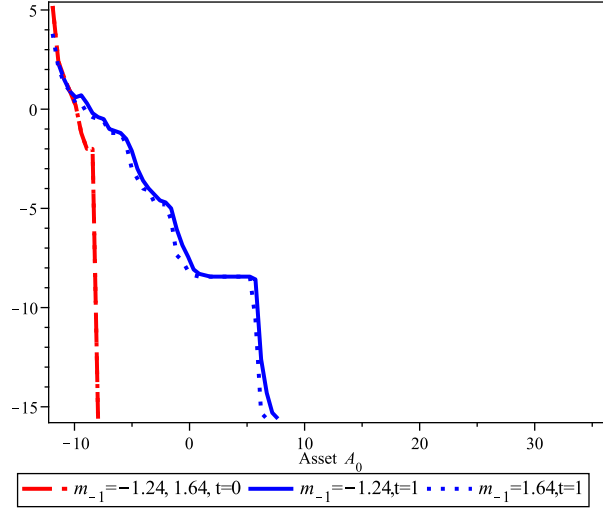


(a) Asset next period in the white-collar state: $E(A_1^w(A_0, m_0 \geq \bar{m}_0(A_0)) | m_{-1})$ with prior m_{-1} fixed

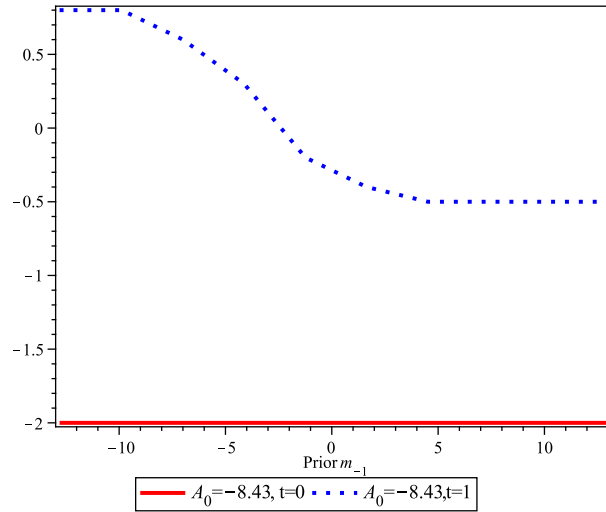


(b) Asset next period in the white-collar state: $E(A_1^w(A_0, m_0 \geq \bar{m}_0(A_0)) | m_{-1})$ with asset A_0 fixed

Figure 2.1: Asset next period in the white-collar state at $t = 1$ (asset unit: 10,000\$)

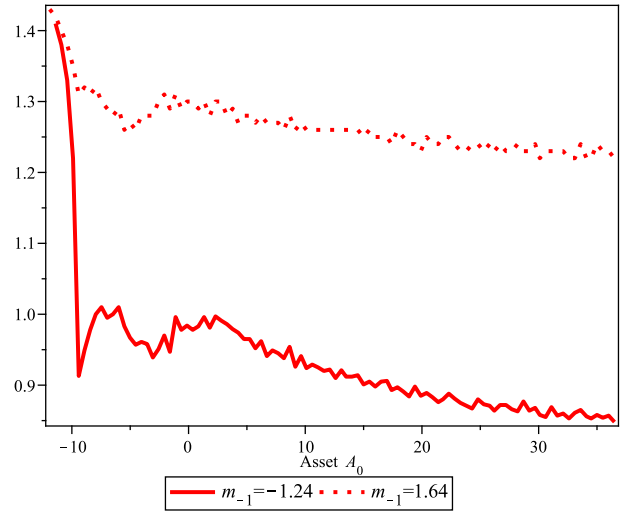


(a) Evolution of ability thresholds: $\bar{m}_0(A_0)$ and $E(\bar{m}_1(A_0, m_0 \geq \bar{m}_0(A_0)) | m_{-1})$ with prior m_{-1} fixed

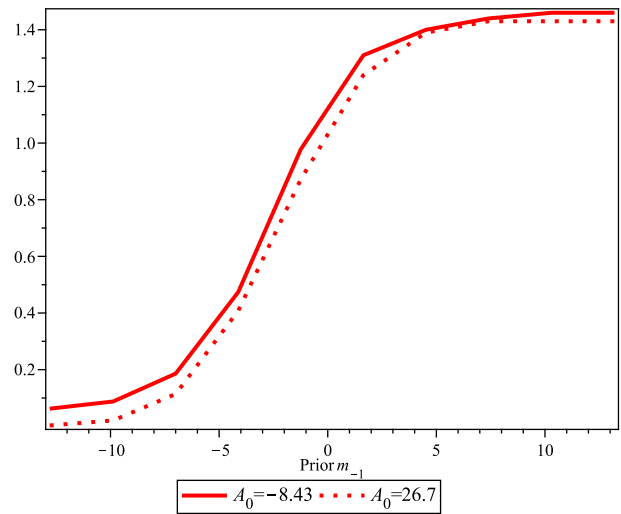


(b) Evolution of ability thresholds: $\bar{m}_0(A_0)$ and $E(\bar{m}_1(A_0, m_0 \geq \bar{m}_0(A_0)) | m_{-1})$ with asset A_0 fixed (parents with high assets have no thresholds at either period yet)

Figure 2.2: Evolution of ability thresholds starting from $t = 1$ (asset unit: 10,000\$)

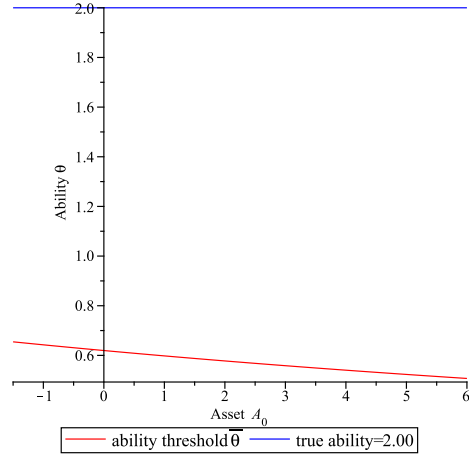


(a) Education saving next period in the white-collar state: $E(A_1^w(A_0, m_0 \geq \bar{m}_0(A_0)) - A_1^b(A_0) | m_{-1})$ with prior m_{-1} fixed

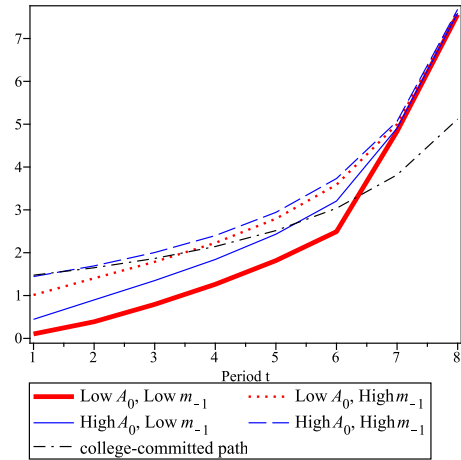
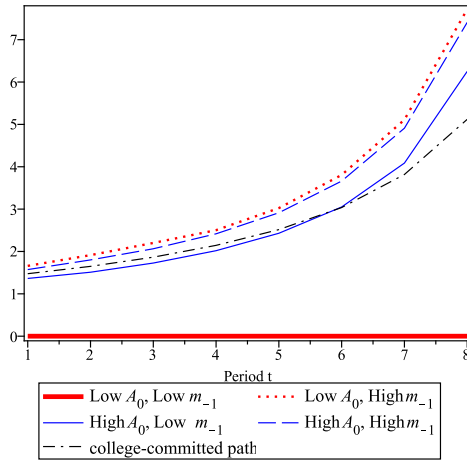


(b) Education saving next period in the white-collar state: $E(A_1^w(A_0, m_0 \geq \bar{m}_0(A_0)) - A_1^b(A_0) | m_{-1})$ with asset A_0 fixed

Figure 2.3: Education saving next period in the white-collar state at $t = 1$ (asset unit: 10,000\$)



(a) Initial ability threshold under full information vs. true ability

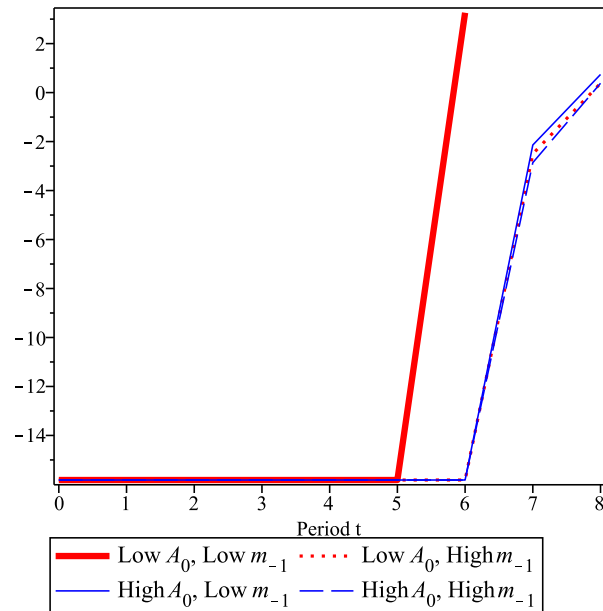


(b) one-period learning: college saving in the white-collar and college-committed states (parents with low A_0 and low m_{-1} actually have no college saving; they are kept for showing the legend and comparison purpose)

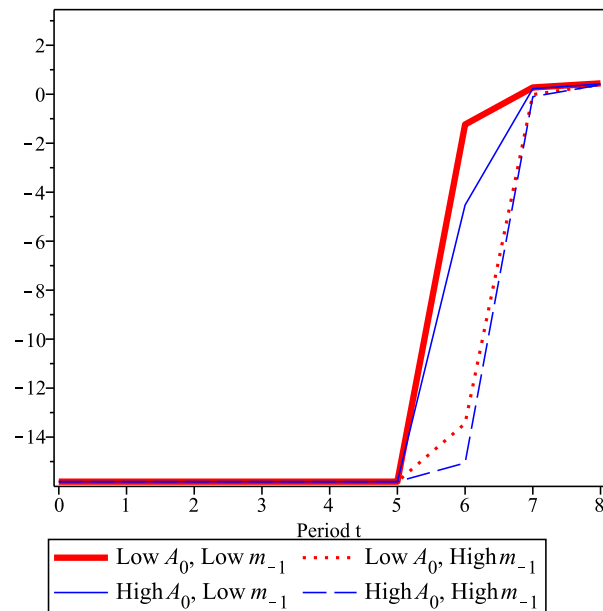
(c) Learning: college saving in the white-collar and college-committed states

College savings under different combinations of initial state variables (asset unit: 10,000\$) and initial ability threshold under full information compared with true ability (High $A_0 = 5$, Low $A_0 = -1$, High $m_{-1} = 1.7$ and Low $m_{-1} = -1.1$)

Figure 2.4: Evolutions of college savings by different models



(a) one-period learning: ability thresholds



(b) Learning: ability thresholds

Ability thresholds under different combinations of initial state variables (asset unit: 10,000\$) and initial ability threshold under full information compared with true ability (High $A_0 = 5$, Low $A_0 = -1$, High $m_{-1} = 1.7$ and Low $m_{-1} = -1.1$)

Figure 2.5: Evolutions of ability threshold by different models

Chapter 3

Empirical evidence on the college saving with learning

3.1 Introduction

This empirical examination focuses on how wealth affects college-bound choice with the presence of learning and how pessimism/optimism determines college saving over time. This is the first investigation on the existence of learning behavior and its interaction with wealth in the context of college saving.

The main prediction about wealth on college-bound choice from the theoretical model in Chapter 2 is that richness A_t can relax parents' college-bound standard (ability threshold $\bar{m}_t(A_t)$) so that there will be more chance to observe parents to expect and save for child's college at $t+1$. This is the **Wealth Effect I**. The identification for this effect arises from these aspects: to identify the college-bound probability change due to wealth, the prior has to be controlled since it also has positive effect on this probability by the **Learning Effect I**. Also, this cross-sectional wealth advantage will diminish over time when the learning reduces the uncertainty on the child's ability.¹ Additionally, these wealth effects can only play the role when parents did not opt out the white-collar state in the previous period. Finally, We should also control

¹Keeping other factors constant, parents should demand less increase in ability threshold in order to balance the loss of consumption utility given same unit of wealth decrease happens every next period. Namely, ability threshold becomes flatter over time. See Footnote ²⁵.

the ability signal because a child with better ability signal should amplify the wealth effect in improving the probability of selecting white-collar state. In a word, I should test the positive wealth effect on the college-bound probability when state dependence of parents' college-bound choice, convergence of wealth effect and ability signal are under control.²

The other control variable is saving in my model. I will investigate the validity of the other important property predicted by the model: saving for college should increase with ability prior, namely the *Learning Effect II*. Simultaneously, wealth effect on college saving will also be explored.

Tests for these two predictions fall into the models of discrete and continuous variable respectively. Naturally, to account for the prior, we should include the lagged dependent variable since the outcome from last period should also be the choice based on the prior. Panel technique is preferred to handle the heterogeneity. Consequently, the dynamic panel models for both discrete and continuous variable are taken for this empirical study. Section 3.2 presents the data used. Section 3.3 analyzes the test specifications and empirical barriers. Section 3.4 and 3.5 discusses the results and summarizes the validity of theoretical model.

3.2 Data

This analysis draws data from the Panel Study of Income Dynamics (PSID), which is a nationally representative sample of households and individuals in the United States. The PSID began in 1968 and presently continues to follow families and individuals. The PSID collects information from both individuals and families, primarily focusing on economics and demographics, including income, employment, family composition, and residential location. I also use data from the Child Development Supplement (CDS) and Transition into Adulthood (TA) to the PSID. With a grant from the National Institute of Child Health and Human Development, researchers for the PSID were able

²The ability prior is borne by the lagged college-bound choice, which will be explained shortly.

to collect extensive data regarding children’s home environment, family, time use at home and school, school and daycare environment, and other cognitive, behavioral, physical, and emotional measures for up to two randomly selected children living in PSID households. Up to three generations of samples are currently available: CDS-I (1997), CDS-II (2002-2003) and TA (2005), which represents wave one to three in this study. CDS-I completed interviews for 3,563 children at 0-12 years old. CDS-II fielded the data collection by following the same children appearing in CDS-I with a final size of 2,907 children aged at 5-18. Finally, TA covers a sample of 760 respondents who were initially in CDS-I, associated with a PSID family in 2005, at least 18 years old and graduated from or no longer attending high school (Mainieri 2006; Stafford et al. 2008).

The empirical study mainly use the data constructed by linking two waves of Child Development Supplement (CDS) and one wave of Transition into Adulthood (TA) from Panel Study of Income Dynamics (PSID) (the target subsample has 174 separate families; detailed data information is available in Appendix A). Full sample contains the children/families from the whole TA sample with younger sibling dropped if existed and observations already enrolled in college at wave two. The number of observations available for each measures ranges from 453 to 630.³ All the members in the target subsample have no missing value for any of the measures listed in Table 3.1 and they follow the same family heads for all the waves. The sample size for this subsample is 172. Table 3.1 contains the summary statistics for both target subsample and the full sample.⁴ Appendix A.2 and A.2.5 provides detailed illustration on variable constructions.

By the author’s awareness, this is the only data which contains the questions on asset holding, college-bound related choice and child’s ability measure when the child is near college age. They cover the state and control variables in my model. The longitudinal nature of this sample can aid for overcoming the difficulties in measuring parents’ belief on child’s ability and controlling unobservable heterogeneity. The former can allow the estimation of learning behavior which implies the switch of college expectation/outcome and/or change of college saving observed over time in response to different ability signals. The latter can restrain the selection due to different preference of

³The raw sample of TA has a sample size of 740.

⁴This target subsample has more number of children, less divorce rate and its variation, higher income and wealth, better test score from child and other signs which means it contains a more stable and better-off set of households. Its response to college expectation and outcome question has a higher mean and smaller standard deviation. In all of these senses, this subsample with small sample size should not be expected to pose systematic bias against my model inquiry about the issue of saving for child’s college under learning.

college choice or college premium. Last but not least, this sample traced the household saving behavior between 1997 and 2005, which is more recent than other data used to capture the growing incentive of college saving due to fast rise of college price.⁵

3.3 Specification and empirical issues

Next, Section 3.3.1 shows the specification for test about college-bound choice and presence of initial condition problem and the solutions involved. Section 3.3.2 covers the specification for test about college saving level and GMM estimator to revolve the endogeneity issue.

3.3.1 Test on college-bound choice

The specification for a test of wealth effect on college-bound choice is a dynamic binary choice model, where the latent dependent variable y_{it}^* is

$$y_{it}^* = \gamma y_{it-1} + \beta_1 A_{it} + \beta_2 (t-1) A_{it} + \nu(t-1) + \eta s_{it} + x'_{it} \delta + \alpha_i + u_{it}, \quad (3.1)$$

where $i = 1, \dots, 174$ and $t = 2, 3$ since the sample has 174 respondents and three waves. y_{it} is the binary choice variable, college-bound choice, defined as $y_{it} = 1$ (white-collar state) if $y_{it}^* > 0$, and 0 (blue-collar state) otherwise. I use a recoded variable of college expectation/outcome from data as proxy for y_{it} . y_{it-1} appears to allow the control of prior since this depends on the posterior formed in the last period which should be directly related with prior.⁶ A_{it} is asset level for family i at time t . To control the flattening of ability threshold over time, the joint term of $t-1$ and A_{it} is included together with the

⁵PSID also keeps higher response rate of 95-98% and fewer missing data for the wealth information (compared to about 10% of missing values in NLSY wealth data; See [Bradley and Corwyn \(2002\)](#) and [Yeung and Conley \(2008\)](#)).

⁶See Appendix A for related description.

time trend $t - 1$. The latter might measure the shift in overall level of belief on child’s ability as well as the college-bound expectation. Ability signal is controlled by a proxy s_{it} , normalized assessment score. α_i is the individual-specific time-invariant unobservable, which can capture ability prior which my model structurally specifies. u_{it} is the error term and $u_{it} \sim N(0, \sigma_u^2)$. All the rest of control variables appear in the vector x_{it} . Most of these variables attempt to catch the impact of psychic cost in schooling choice discussed by Heckman et al. (2006), Cunha et al. (2005) and Cunha and Heckman (2008).⁷ Keane and Roemer (2009) analyze the cause of psychic costs due to difference in taste and/or efforts with respect to preparation for college.⁸ The other important control variable is the assessment of college expenditure when college attendance probability, average yearly college expenditure for different type of college, state of residence and year of measurement are considered. This is to acknowledge that parents might also use the rational forecast of future college cost when forming college-bound choice. In equation (3.1), the main interests lie in β_1 and β_2 , which represent the positive wealth effect on college-bound choice and its convergence over time. γ captures the state dependence of college-bound choice and η reveals the impact of new information every period on forming the choice.

The presence of unobservable heterogeneity causes two problem: firstly, the composite error term, $v_{it} = \alpha_i + u_{it}$, is correlated over time due to α_i . For example, the very beginning prior on child’s ability will be carried on when parents repeatedly update belief and make college-bound choice. The standard solution is the random effect (RE) model.⁹ As documented in Greene (2005), RE model is much more tractable than fixed effect (FE) one. Unlike the linear model, FE binary choice model cannot use differencing or mean deviation transformation to remove the individual dummy. Besides this computational complexity, the notorious incidental parameters problem also arises. In a short panel with small T_i , the number of parameters increases with N . The estimation will be subject to small sample bias. However, RE model assumes α_i uncorrelated with all the explanatory variables, which can be too restrictive.

⁷See 1(b) below Table 3.2 for the coverage of controls. They cover almost all the variables, mentioned by these recent studies, related with psychic costs. The only exclusion is child’s grade because it has perfect collinearity with college expectation/outcome in last wave by construction.

⁸Keane and Roemer (2009) discuss, for instance, the relationship between parents’ education with college choice:“(i) youth with less educated parents may have less taste for college attendance, partly because it was not inculcated in their youth, partly because it would involve deviating from behavior of their peers, (ii) academic pursuits may be frowned upon in less educated families, (iii) youth with less educated parents may be poorly prepared for college, so attendance would take more effort.”

⁹I apply the RE probit model. The result from a RE logit model is very close.

Honore and Kyriazidou (2000) proposes a fixed effect specification for dynamic binary choice model. However, the assumption of a single regressor precludes my application. Mundlak (1978) and Chamberlain (1984) allow the correlation between α_i and either the time means of the time-variant explanatory variables or a combination of their lags and leads. Secondly, the combination of unobservable heterogeneity and state dependence can cause an “initial conditions” problem and result in inconsistent estimates of the structural parameters, particularly the state dependence. As documented in Heckman (1981) and Chay and Hyslop (1998), there are two sources of state dependence: one is the structural persistence as predicted by my model and measured by γ and the other is heterogeneity. The latter, in my model, includes those observables, such as psychic cost, college cost information, asset and ability signal, and unobservables, such as ability prior and possible serial correlation in error terms. The main issue lies in the correlation between ability prior contained in α_i and initial college-bound choice y_{i1} . Heckman (1981), Greene (2003) and Chay and Hyslop (1998) have showed misspecifying the sample initial conditions due to unobservability of pre-sample history is the stateogen. The seriousness dramatically increases when time series is short.

With the strong assumption that initial observations y_{i1} to be independent with α_i , *e.g.* ability prior, the model can be estimated by random effect probit model where the likelihood contribution by individual i at t is

$$\Pr(y_{it}|x_{it}, y_{it-1}, \alpha_i) = \Phi\{(\gamma y_{it-1} + w'_{it}\xi + \alpha_i)(2y_{it} - 1)\},^{10} \quad (3.2)$$

where w_{it} is a vector including all the rest of regressors in (3.1) except y_{it-1} and α_i . However, college-bound choice at wave one is structurally dependent on prior. I use the approach proposed by Heckman (1981) to specify a reduced-form equation for initial condition $y_{i1}^* = y_{i1}\pi + \tau\alpha_i + u_{i1}$, where y_{i1} is a vector of exogenous instruments (containing x_{i1})¹¹. The likelihood function is obtained by

$$\prod_i \int_{\alpha^*} \left[\Phi\{(y_{i1}\pi + \tau\sigma_\alpha\alpha^*)(2y_{i1} - 1)\} \prod_{t=2}^3 \Phi\{(\gamma y_{it-1} + w'_{it}\xi + \sigma_\alpha\alpha^*)(2y_{it} - 1)\} \right] dF(\alpha^*), \quad (3.3)$$

where $\alpha_i \sim N(0, \sigma_\alpha^2)$ and F is the distribution function of $\alpha^* = \alpha_i/\sigma_\alpha$, the inte-

¹⁰For a detailed discussion on the estimation of dynamic probit model with RE, see Stewart (2006), from which I borrow most of the notations on model specifications and use his **redprobit** and **redpace** module in *Stata* for the implementation of Heckman’s estimator and its extension with AR1 errors.

¹¹Besides, I also use BPI (behavior problem index) measured in wave one since the simple probit estimation shows significant effect from it.

gral is evaluated by Gaussian-Hermite quadrature (Butler and Moffitt 1982). If there is no autocorrelation of u_{it} , this Heckman’s estimator can render consistent results. Otherwise, this is not true, particularly when the model is exposed to a learning process. Then, I implement another estimator following Hyslop (1999) to extend Heckman estimator by integrating a high-dimensional normal distribution. Similarly, I use Maximum Simulated Likelihood (MSL) based on the Geweke-Hajivassiliou-Keane (GHK) algorithm (Keane 1994) to approximate the expectations.¹² AR1 process is specified: $u_{it} = \rho u_{it-1} + \epsilon_{it}$. To explore the learning effect, I also carry each specification on a contrast case when normalized assessment score s_{it} is dropped. All the specifications are estimated with both asset with housing and asset without housing.

Furthermore, the Mundlak correction suggested in the beginning of this section is adopted to explore the possible correlation between individual unobservable and independent variables. This approach simply incorporates the means of the time varying variables into the regressors. I implement this over all of the panel specifications discussed above.

3.3.2 Test on college saving level

The test on both effects of wealth and belief on college saving is given as

$$w_{it} = \pi_1 w_{it-1} + \kappa_1 s_{it} + \zeta c_{it} + \kappa_2 c_{it} s_{it} + \pi_2 c_{it} w_{it-1} + x'_{it} \delta + \alpha_i + u_{it}, \quad (3.4)$$

where $i = 1, \dots, 174$ and $t = 1, \dots, 3$. For each family i at period t , w_{it} is the log-transformed asset level, s_{it} normalized assessment score, c_{it} college expectation/outcome, x_{it} the vector of control variables, α_i the individual-specific time-invariant unobservable and u_{it} the error term and $u_{it} \sim N(0, \sigma_u^2)$.¹³ As discussed previously, the lagged asset/saving level is included since it has the information of prior.¹⁴ π_1 measures the regular life-cycle saving motive except preparation for child’s college, where the latter is caught by π_2 . To capture the belief effect on college saving, I use the combination of single regressor about assessment score s_{it} and its joint term with college expectation/outcome c_{it} . The single term plus other control variables and individual-specific heterogeneity α_i should work together as a control of ability posterior which determines

¹²The GHK algorithm transforms the probability of an observed sequence of random variable as the product of recursively defined conditional probability, which can be much easier for forming simulated expectation (Stewart 2006).

¹³The log-transformation for asset is $w_{it} = \ln(\hat{w}_{it} + 1)$ if $\hat{w}_{it} \leq 0$ and $-\ln(-\hat{w}_{it} + 1)$ otherwise, where \hat{w}_{it} is the raw value. x_{it} shares the same variables as those in equation (3.1) plus child’s grade. See 1(b) below Table 3.2 for the coverage.

¹⁴Section 4.4 will offer the other well-documented motive, inertia, for this dynamic specification in the saving literature.

asset holding w_{it} by my model. After posterior is controlled, the better quality of ability signal s_{it} implies the lower ability prior held by pessimistic parents, who view the signal as a big shock. Therefore, κ_2 should measure the inverse effect of prior on college saving and κ_1 accounts for the effect from posterior. In addition, ζ estimates the change of saving behavior due to switch of college-bound choice only.

This is a dynamic panel data model, where lagged dependent variable is correlated with the disturbance. This renders the inconsistency by standard estimation of either fixed or random effect model which adopts first differences in the first step to remove individual specific α_i :

$$\Delta w_{it} = \pi_1 \Delta w_{it-1} + \kappa_1 \Delta s_{it} + \zeta \Delta c_{it} + \kappa_2 \Delta c_{it} s_{it} + \pi_2 c_{it} \Delta w_{it-1} + \Delta x'_{it} \delta + \Delta u_{it}. \quad (3.5)$$

But Δw_{it-1} is correlated with Δu_{it} , plus the first difference of the predetermined variables also become endogenous.¹⁵ [Arellano and Bond \(1991\)](#) proposes the solution to use the appropriately lagged dependent variables and lagged levels of predetermined variables as instrument to form generalized method of moments (GMM) estimator. Therefore, in my case, every observation in the third wave would have two observations of the dependent variable as instruments,¹⁶ three observations on the predetermined variables as instruments, and all observations on the exogenous variables. To account for the weak instrument issue of lagged levels for first differences, [Arellano and Bover \(1995\)](#) introduced the main level equation (3.4) into the system of equation estimated. I further specify a two-step estimator to firstly achieve a covariance matrix robust to panel-specific autocorrelation and heteroskedasticity, use it to update the initial weighting matrix and then implement GMM again.¹⁷ Both asset including housing and asset excluding housing are tested.

¹⁵No. of children, urbanicity, \ln total income $[t]$ and normalized assessment score are suspected to be predetermined. They might be related with the previous shocks for the history of saving decision.

¹⁶They are from wave zero and one.

¹⁷Section 4.4.2 presents a detailed discussion on the ‘system GMM’ method.

3.4 Results

3.4.1 College-bound choice

Table 3.2 and 3.3 displays the estimate result for the model specified by equation 3.1. They are the estimates of wealth, learning and state dependence on college expectation/outcome under different specifications and asset measures discussed previously.¹⁸ The control variables incorporated are discussed under these tables along with the definition of all the parameters presented and issues of model comparatione.

[insert Table 3.2 and 3.3]

Including asset excluding housing as the regressor, Table 3.2 demonstrates that the estimates of the structural parameters under all the specifications do exhibit the correct sign predicted by the model. College expectation $t - 1$ bears a positive coefficient γ , illustrating the existence of state dependence. In the context of learning, this is postulated to contain the updated belief up to last period. The coefficient of Assessment score η is positive too. Parents do make college bound inference by observing the child's ability signal. All in all, the framework of bayesian learning can reasonably explain the mechanism of college-bound expectation as the estimates suggest. The positiveness of β_1 illustrates the richness does lower the selectivity as the **Wealth Effect I** infers. The joint term of $t - 1$ and asset renders a negative coefficient β_2 . This assures the ability ability threshold tends to flat out over time due to the convergence of belief distribution. The negativity of time trend coefficient ν reveals the plausible initial overestimate of the child's ability in this sample. This implication echoes the similar observation drawn from the statistics of the dynamics of college-bound expectation shown in Table 2.3.

In terms of specifications, we can firstly compare different models under the RE assumption. The first pooled probit estimates disallow any cross-correlation between the composite error terms for individual i across different

¹⁸The number of Gaussian-Hermite quadratures used for evaluating the expectation in Heckman's estimator is 30. That of random number draws for calculating the MSL in the extended AR1 model is 200 for each expectation. I also check the results in other setting: the other number of quadratures for experiment includes 25, 100 and 200; that of random draws are 100, 300, and 1000. The robustness of the results is confirmed.

periods. Thus, all the estimated coefficients of structural variables are larger in absolute term than the other estimators except when serial autocorrelation is controlled. Random effect probit estimator reduces the estimates and significance of these structural parameters, particularly γ . The quaslikelihood-ratio statistic for a test on the existence of random effect is 4.48, which is significant under 5% levels.¹⁹ Exogeneity measure of the initial condition τ turns out to be zero. A quaslikelihood-ratio test of imposing $\tau = 0$ can be easily done by comparing the total log-likelihood between RE probit and Heckman's estimators. The outcome is obviously to reject the hypothesis on endogeneity of initial condition. According to my model, these evidences suggest that all of these control variables used form a good proxy for the ability prior in the beginning of first wave. When the serial autocorrelation in the error term is controlled in Heckman's estimator, significance of almost all the coefficients increases. The magnitude of state dependence parameter γ rises because of the significantly negative autocorrelation presented by ρ .

These cross-specification comparisons can be exactly applied to FE models with Mundlak correction. The outcome is similar. The Heckman estimators with AR1 considered enjoy the highest total log-likelihood in both FE and RE models. Then a likelihood ratio test strongly favors the FE model. When group means are included in the Mundlak correction, the significance and magnitude of the coefficient of assessment score η drops dramatically. On the other hand, only the group mean of assessment score is significant and positive among all the group means in the FE estimate with Mundlak correction. This suggests prior belief plays a vital role in the college-bound choice so that unexpected shock carried by abnormally high or low assessment score might only produce limited impact.

The exactly same tests are implemented when asset including housing is inserted instead. All of the results are similar to those from asset excluding housing except the wealth effect. Table 3.3 reports the most preferred specification - Heckman estimator with AR1 controlled. The coefficient of asset β_1 becomes negative and that of the joint term β_2 turns to be positive although they are not significant. Two aspects of reasons might explain this: buying house in good school district is a popular approach to raise the child's college-bound prospect. But there is strong self-selection such that the parents worrying about the college-bound prospect will be more likely to do so. On the other hand, housing rich might not be truly rich given the sample periods runs between 1997 to 2005, when US house prices underwent an unprecedented

¹⁹They are calculated as twice of the difference of total log-likelihood between alternative models listed at the bottom of Table 3.2 (pooled probit vs. RE probit). The limiting distribution of this statistic is $\chi^2(1)$ (Godfrey (1988) and Andrews (2001)).

increase.

To further examine the importance of state dependence and convergence of wealth effect over time, I supply two alternative specifications when y_{it-1} and $(t-1)A_{it}$ together with time trend $t-1$ are dropped respectively from equation (3.1). Since Heckman estimator with AR1 errors under FE assumption is preferred by quaslikelihood ratio test, the alternative specifications are all modeled by this model. The asset measure is the one excluding housing. Table 3.4 shows the result.

[insert Table 3.4]

Two alternative specifications are strongly rejected by the likelihood ratio test, particularly the one ignoring state dependence in column [1]. All the structural parameters become smaller in magnitude and much less significant. This emphasizes that the incentive to learn the child’s cognitive ability highly depends on whether parents hold the college-bound expectation, and flattening of ability threshold does exist.

3.4.2 College saving

Table 3.5 reveals the test result of wealth and belief effects on college saving.²⁰ This is the estimate for the specification in equation 3.4.

[insert Table 3.5]

Initially, the asset measure includes housing, which corresponds to the total asset concept. π_2 is significantly negative at 1% level, which confirms the dominance of the **Wealth Effect III** induced by less incentive to invest college-bound option as wealth level grows.

The saving decision involving housing can be approximately interpreted by the model of one-period learning when college saving is considered. Household can not hold real property in a sensitive way with respect to child’s ability shock given its lack of liquidity. As discussed previously, when learning effect is not strong, the **Wealth Effect III** might dominate: equation (2.11) shows, given asset level, the first term converges to zero but not the second term when prior is large enough, which is shared by very optimistic parents. There is only insignificant value to secure the child’s college-bound chance by a marginal increase of wealth (decrease of ability threshold) since they are too confident to expect a bad quality child. But the extra expected gain from children “in

²⁰Both Arellano and Bond autocorrelation tests for the level equations and the Sargan test do not indicate misspecification. Section 4.4.2 will explain these two tests.

the money” is too small since they are almost certain in college outcome. It is also very natural to claim that parents holding home equity should be more confident about child’s prospect. And a lot of confident parents buy housing for the hope to use home equity loan to relax the borrowing constraint towards college cost.²¹ All of these may explain the existence of the ***Wealth Effect III*** when effect from asset including housing is tested, while the test outcome using asset excluding housing has reverse sign and is highly insignificant.

The regular saving incentive captured by π_1 is significantly positive at 3% level. It also suggests a negative asset growth rate, which matches the wealth effect explained by typical finite-horizon saving model: richer household (with positive asset) deaccumulates wealth and poorer one (with negative asset) accumulates wealth over time so that wealth levels tend to converge. Additionally, the extra wealth effect from college saving π_2 reinforces this convergence dramatically.²² The college saving is averagely positive at significant level 1% as measured by ζ . For a household with average child and zero asset, the average stock value of college saving from 1997 to 2005 is around \$1,200 in this sample.²³ However, when wealth for this same household rises to the average level in this sample, the average amount of college saving is only \$0.82.²⁴ This finding of positive college saving adds the effort to the long-time debate on implicit financial aid tax as saving disincentive (Dick et al. 2003; Edlin 1993; Feldstein 1995). My result suggests a rejection on the impact of this tax can be caused by controlling the heterogeneity involved in family’s college saving behavior, particularly when their college-bound expectation together with learning aspect is measured. Long (2004), Monks (2004) and Reyes (2007) also turn down the evidence of this tax effect from prior literatures by arguing the large changes on federal and institutional aid system has happened. They suggest to incorporate more detailed measures on families’ college-bound expectation process which can cause huge disparity in estimation.

Using asset including housing, the effect from learning is highly insignificant. But it turns to be opposite when asset excluding housing is inserted instead. Both estimates of κ_1 and κ_2 significantly obtain the sign predicted by my model. This contrast can be explained by the evidence from the test

²¹Booming housing market during 1997-2005 period covered in our data can strengthen this motive. These families tend to be more stable, better-off in living standard, more educated and more actively and earlier invest in child’s human capital.

²²Since the year gap between waves in the sample are different so that it is not straightforward to achieve the estimate of growth rate.

²³Namely, $e^{7.09}$. By the construction of normalized assessment score, the average person in population has this score zero. Zero asset level is at 7.9 percentile in this sample.

²⁴Namely, $e^{7.09+9.85 \times (-0.74)}$, where 9.85 is the mean of Ln asset incl. housing[$t - 1$] in the sample.

on college-bound choice that asset excluding housing should be more liquid to respond to the information observed from child's ability signal over time.

The other interesting result is that two tests render the coefficients and significance in opposite way always. This can support the conjecture that family are involved with reallocation of asset portfolio to shield away from the possible aid tax or child's ability risk (Reyes 2007) by hedging among different asset categories. The total college expectation seems significantly negative for asset excluding housing. Parents might play aid tax game in other asset category since home equity has been removed from the calculation on family's ability to pay tuition by Federal Methodology. This determines the distribution of Federal funds, including both grants and loans. Next section will provide further explanation about the wealth effect on college saving from our empirical evidence.

3.5 Conclusion

In summary, test on college-bound choice confirms the positive effect from asset and its convergence over time. The state dependence of college-bound choice is significant particularly when autocorrelation due to learning is controlled. There is strong support for existence of parents' learning behavior when preparing child's college cost. Test on college saving level shows confident parents respond more positively in increasing additional saving induced by college-bound expectation when only assets excluding housing are considered.

Table 3.1: Summary statistics of PSID/CDS & TA (1997-2005)*

	<i>Target subsample</i>		<i>Full sample</i>	
	Mean	Std Dev	Mean	Std Dev
<i>Demographics</i>				
Child's race(1=white 0=black)	0.67	0.47	0.54	0.5
Child's age (wave 1)	10.59	0.95	10.83	1.04
Child's grade (wave 1)	4.16	0.89	4.59	1.11
Child's grade (wave 2)	9.93	0.83	9.89	0.89
Child's grade (wave 3)	11.63	1.16	11.28	1.44
Mother's yr of education (wave 3)	13.74	2.19	13.07	2.47
Mother's age (wave 1)	39.45	5.19	38.62	5.45
# of children (wave 1)	2.45	0.86	2.45	1.05
# of children (wave 2)	2.51	1.32	2.35	1.68
# of children (wave 3)	3.01	2.45	2.48	2.2
Parent divorced (wave 1)	0.09	0.29	0.13	0.33
Parent divorced (wave 2)	0.09	0.29	0.16	0.36
Parent divorced (wave 3)	0.09	0.29	0.17	0.37
<i>Financial characteristics</i>				
Total income \$ (wave 1)	77,270	72,132	61,003	72,470
Total income \$ (wave 2)	97,089	110,701	69,481	82,044
Total income \$ (wave 3)	97,787	124,497	67,141	84,500
Asset excluding housing \$(wave 0)	116,640	430,833	80,870	345,573
Asset excluding housing \$ (wave 1)	253,884	1,411,523	135,900	794,734
Asset excluding housing \$ (wave 2)	391,738	2,527,072	181,047	1,374,728

Continued on next page

Table 3.1: Summary statistics (continued)

	<i>Target subsample</i>		<i>Full sample</i>	
	Mean	Std Dev	Mean	Std Dev
Asset excluding housing \$ (wave 3)	334,533	2,335,689	170,033	1,286,806
Asset including housing \$ (wave 0)	162,508	486,237	114,506	373,190
Asset including housing \$ (wave 1)	306,683	1,460,308	177,863	828,142
Asset including housing \$ (wave 2)	479,540	2,623,473	242,813	1,431,619
Asset including housing \$ (wave 3)	443,431	2,415,851	241,448	1,338,525
<i>Others</i>				
Normalized assessment score (wave 1)	0.14	0.76	-0.11	0.82
Normalized assessment score (wave 2)	-0.03	0.9	-0.37	0.92
Normalized assessment score (wave 3)	-0.04	1.09	-0.14	1.04
Urbanicity (wave 1; 10 = Most rural, 1 = most urban)	2.7	2.2	2.71	2.22
Urbanicity (wave 2; 10 = Most rural, 1 = most urban)	3.31	2.31	3.39	2.42
Urbanicity (wave 3; 10 = Most rural, 1 = most urban)	3.32	2.28	3.42	2.42
Yearly college expenditure \$ (wave 1)	8,325	2,899	8,428	3,120
Yearly college expenditure \$ (wave 2)	10,072	3,071	10,042	3,220
Yearly college expenditure \$ (wave 3)	10,585	3,212	10,611	3,393
Child's behavior problem index	38.38	6.98	40.78	8.98
College expectation/outcome (wave 1; 1=college 0=non-college)	0.86	0.35	0.77	0.42
College expectation/outcome (wave 2; 1=college 0=non-college)	0.93	0.26	0.75	0.43
College expectation/outcome (wave 3; 1=college 0=non-college)	0.85	0.36	0.66	0.47

Source: PSID/CDS & TA

* See Appendix A for details.

Table 3.2: Estimated effects of state dependence, wealth and learning on college expectation/outcome¹
- I. Asset regressor excludes housing

Variable ²	Pooled probit			Random effect probit			Heckman's estimator			With AR(1) errors		
	(SE)	RE ³	(SE)	FE	RE	(SE)	FE	RE	MSL (SE)	FE	RE	FE
College exp $[t - 1]$: γ	1.055*** (0.245)	0.653** (0.362)	0.411 (0.492)	0.411 (0.492)	0.628** (0.376)	0.377 (0.519)	0.411 (0.492)	0.628** (0.376)	1.568*** (0.353)	0.377 (0.519)	1.568*** (0.353)	1.472*** (0.388)
Asset: β_1	0.103** (0.051)	0.087* (0.061)	0.070 (0.075)	0.070 (0.075)	0.08* (0.061)	0.065 (0.076)	0.070 (0.075)	0.08* (0.061)	0.112** (0.060)	0.065 (0.076)	0.112** (0.060)	0.119** (0.070)
$(t - 1) \times$ Asset: β_2	-0.072** (0.034)	-0.062** (0.040)	-0.051 (0.048)	-0.051 (0.048)	-0.057* (0.040)	-0.047 (0.048)	-0.051 (0.048)	-0.057* (0.040)	-0.075** (0.041)	-0.047 (0.048)	-0.075** (0.041)	-0.072** (0.047)
$t - 1$: ν	-0.020 (0.384)	-0.049 (0.472)	-0.260 (0.636)	-0.260 (0.636)	-0.073 (0.482)	-0.297 (0.658)	-0.260 (0.636)	-0.073 (0.482)	-0.005 (0.466)	-0.297 (0.658)	-0.005 (0.466)	-0.148 (0.534)
Assessment score: η	0.223** (0.098)	0.194** (0.124)	0.004 (0.174)	0.004 (0.174)	0.192** (0.126)	0.009 (0.177)	0.004 (0.174)	0.192** (0.126)	0.225** (0.126)	0.009 (0.177)	0.225** (0.126)	0.068 (0.171)
Random effect: λ		0.395** (0.233)	0.581** (0.229)	0.581** (0.229)	0.419* (0.235)	0.605*** (0.229)	0.581** (0.229)	0.419* (0.235)	0.359** (0.143)	0.605*** (0.229)	0.359** (0.143)	0.39*** (0.143)
Exogeneity measure: τ					0.000 (0.001)	0		0.000 (0.001)	0.000 (0.000)	0	0.000 (0.000)	0.000 (0.000)
AR(1) coefficient: ρ									-0.713*** (0.138)		-0.713*** (0.138)	-0.685*** (0.144)
No. of obs.	348	348	348	348	522	522	348	522	522	522	522	522
Model log-likelihood	-94.42	-93.13	-86.54	-86.54	-141.36	-135.00	-86.54	-141.36	-137.26	-135.00	-137.26	-132.83
Total log-likelihood	-144.89	-143.60	-137.01	-137.01	-141.36	-135.00	-137.01	-141.36	-137.26	-135.00	-137.26	-132.83

¹ (a) significance level: *** 1%, ** 5% and * 10%; (b) the control variables include mom's yrs of edu, child's age, child's race, mom's age, no. of children, urbanicity, yearly college expenditure, parents divorced and \ln total income $[t - 1]$; Continued below Table 3.3.

Table 3.3: Estimated effects of state dependence, wealth and learning on college expectation/outcome¹
- II. Asset regressor includes housing

Variable ²	With AR(1) errors	
	RE ³	FE
College exp.[$t - 1$]: γ	1.482*** (0.365)	1.327*** (0.415)
Asset: β_1	-0.052 (0.106)	-0.005 (0.127)
$(t - 1)$ ·Asset: β_2	0.027 (0.064)	0.027 (0.078)
$t - 1$: ν	-1.018 (0.733)	-1.195 (0.880)
Assessment score: η	0.266** (0.127)	0.063 (0.176)
Random effect: λ	0.384** (0.153)	0.434*** (0.152)
Exogeneity measure: τ	0.000 (0.000)	0.000 (0.000)
AR(1) coefficient: ρ	-0.676*** (0.152)	-0.653*** (0.161)
No. of obs.	522	522
Model log-likelihood	-140.06	-133.87
Total log-likelihood	-140.06	-133.87

¹ (a-b) See 1 below Table 3.2; (c) to account for the different normalizations on error term between pooled probit and all the random effect models, this table shows all the rescaled estimates by multiplying the raw results by $\sqrt{1 - \lambda}$ except those from pooled probit.

² The first five structural parameters are specified in equation (3.1). λ is the ratio between the variance of individual-specific RE effect α_i and that of composite error: $\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}$, τ is specified as exogeneity measure in equation (3.3) and ρ is AR1 coefficient for u_{it} .

³ RE: only the random effect individual unobservable is modeled; FE: fixed effect is also controlled by Mundlak correction (Mundlak 1978).

⁴ For the purpose of cross specification comparison, the total log-likelihood of either pooled probit or random effect probit models is the sum of the model log-likelihood at $t \geq 2$ (348 observations) and log-likelihood of a simple probit from reduced form specification at $t = 1$ (174 observations). Critical value of $\chi^2(1)$: 1% - 5.412, 5% - 2.706, 10% - 1.642.

Table 3.4: Alternative specifications: existence of state dependence and convergence of wealth effect on college expectation/outcome^{*}

Variable	Baseline (SE)	[1] (SE)	[2] (SE)
College exp. $[t - 1]$: γ	1.472*** (0.388)		1.268*** (0.387)
Asset: β_1	0.119** (0.070)	0.055 (0.090)	0.015 (0.034)
$(t - 1)$ ·Asset: β_2	-0.072** (0.047)	-0.041 (0.057)	
$t - 1$: α	-0.148 (0.534)	-0.336 (0.757)	
Assessment score: η	0.068 (0.171)	-0.009 (0.194)	0.036 (0.171)
No. of obs.	522	522	522
Model log-likelihood	-132.83	-138.62	-137.85
Total log-likelihood	-132.83	-138.62	-137.85

^{*} (a) All the specifications are implemented by the Heckman estimator with AR1 errors. The baseline model is exactly the last column in Table 3.2. The column [1] corresponds to the model with state dependence effect omitted and [2] to the model with convergence of wealth effect and time trend omitted; (b) refer to 1 and 2 below Table 3.2 and 3.3 for the issues of significance levels, control variables, rescaling and definition of parameters and 3 for the calculation of total log-likelihood which are also shared in this table.

Table 3.5: Estimated effects of wealth and belief on college saving¹

Variable	Asset incl. housing ²		Asset excl. housing ³	
	Coef. (SE)	P value	Coef. (SE)	P value
Asset $[t - 1]^2$: π_1	0.67 (0.30)	0.03	-0.35 (0.32)	0.28
Assessment score: κ_1	-0.18 (0.64)	0.78	3.52 (1.39)	0.01
College exp.: ζ	7.09 (2.83)	0.01	-3.92 (2.41)	0.11
College exp. \times Assessment score: κ_2	0.01 (0.74)	0.99	-3.98 (1.65)	0.02
College exp. \times asset $[t - 1]$: π_2	-0.74 (0.28)	0.01	0.10 (0.34)	0.76

¹ See 1(b) below Table 3.2 for the coverage of most control variables. The only extra one is child's grade.

² Asset measures are asset including housing. The value is logarithmized. After experimenting, the classification of instruments is: the endogenous variables are asset $[t - 1]$ and assessment score, the predetermined ones are moms yrs of edu, childs age, childs race, moms age, no. of children, urbanicity, yearly college expenditure, parents divorced, child's grade, ln total income $[t - 1]$, college exp., college exp. \times assessment score and college exp. \times asset $[t - 1]$, and the strictly exogenous one is time dummies. Arellano and Bond autocorrelation tests for the level equations: $z = 0.43$ and $\Pr > z = 0.699$ for AR(1) test and $z = 1.31$ and $\Pr > z = 0.190$ for AR(2) test. The Sargan test shows $\chi^2(42) = 77.00$ and $\Pr > \chi^2(42) = 0.001$.

³ Asset measures are asset excluding housing. The value is logarithmized. After experimenting, the classification of instruments is: the endogenous variables are asset $[t - 1]$, assessment score, moms yrs of edu, moms age, no. of children, parents divorced and urbanicity, the predetermined ones are child's grade, ln total income $[t - 1]$, college exp., college exp. \times assessment score and college exp. \times asset $[t - 1]$, and the strictly exogenous ones are time dummies, childs age, childs race and yearly college expenditure. Arellano and Bond autocorrelation tests for the level equations: $z = 1.18$ and $\Pr > z = 0.240$ for AR(1) test and $z = 1.84$ and $\Pr > z = 0.065$ for AR(2) test. The Sargan test shows $\chi^2(42) = 68.70$ and $\Pr > \chi^2(42) = 0.000$.

Chapter 4

Education saving propensity and education saving accounts

4.1 Introduction

In recent decades, the government has introduced two tax-favored education saving accounts (ESAs): the 529 plan and the Education IRA (recently renamed the Coverdell Education Savings Account). Contributions to these education saving instruments are not deductible for federal tax purposes, but qualified withdrawals are exempt from federal income tax. By the year end 2002, assets had grown to 19.2 billion and are estimated to reach \$85 billion by 2006. The total number of Section 529 accounts increased from 500,000 in 1996 to 2.6 million in 2001 to 9.3 million in 2006 to 11.2 million in 2008 and 2009 (Baum et al. 2009). Batchelder et al. (2006) has suggested there is not enough study devoted to the implication of economic efficiency driven by these tax-favored vehicles. Many tax benefits are biased towards higher-income households which can reduce economic efficiency since such households might not be more responsive to the tax advantages in producing behavior with larger social benefits. Likewise, the important empirical question on ESA is whether the households with demand on education saving really utilize ESA and how this association can vary due to income difference. The optimal tax policy should be designed to encourage households with stronger education

saving propensity (ESP) to more aggressively contribute to ESA.¹ To provide more fiscal help on these households, government can improve the economic efficiency in the investment of human capital.

This study contributes to the discussion on the economic efficiency of ESA by the supplement of an investigation aided by the panel technique on a national data. The result also provides a stage for the policy application of my theoretical model. Only a few of literature have studied this burgeoning area. [Dynarski \(2004\)](#) finds investors in 529 plans or Coverdell Education Savings Accounts have substantial savings in other vehicles and represent a relatively elite group. ESA as tax-waive tool is more frequently used by the rich household though they may not have enough ESP. Participation in tax-favored saving programs may be only attributed to the stronger propensity to save. Therefore, there may not be an appropriate way to measure the substitution effect between ESA and other forms of savings, which is usually emphasized in retirement saving literature ([Poterba et al. 1996](#)). If the household actively resorts to ESA truly for ESP, it is likely to crowd out IRA by ESA particularly among low income households.² However, [Ma \(2003\)](#) suggests that ESA in general do not offset other household saving and stimulate saving for households which have high propensities to use it.

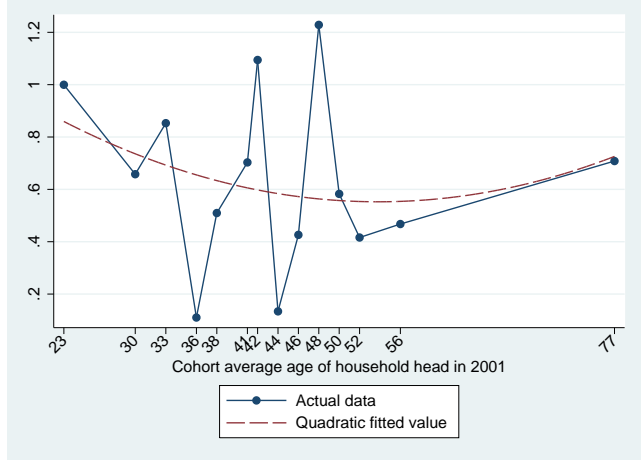
On the other hand, saving incentive is difficult to measure. [Engen et al. \(1996\)](#) elaborated on the barriers: First, saving behavior varies significantly across households. Second, saving and wealth are net concepts: the data show that households with saving incentives have taken on more debt than other households. Third, financial markets, pensions and Social Security have undergone major changes since the expansion of tax-favored saving instruments including IRAs, 401(k)s and ESA. Fourth, a given balance in a saving incentive account represents less long-term saving, defined either as reduced previous consumption or deferred consumption, than the same balance in a conventional account.

Figure 4.1 reveals the deviation between the households contributing to ESA (ESA cohort) and those with strong saving propensity for education (ESP cohort) through the (log) difference in the mean income and their overlapping over 14 age-cohorts with almost equal size in Survey of Consumer Finance (SCF) 2001-2007.³ In one question about saving attitude, the household is supposed to answer what their most important reasons for saving are. Among a

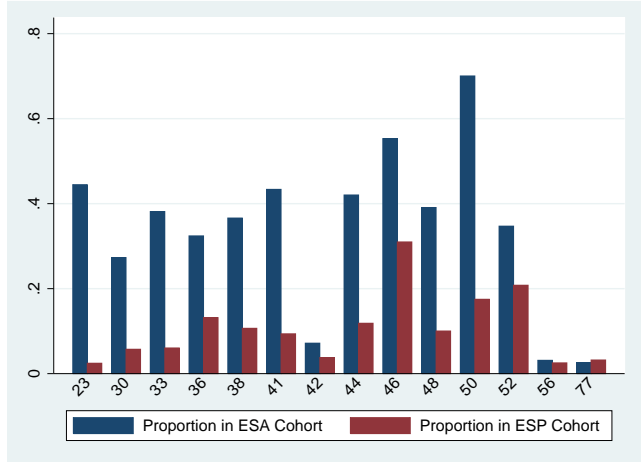
¹Note this propensity differs from *tax incentive*. The former is the desire to accumulate wealth for the prospective education related expenditure. The latter is the deduction, exclusion or refunds provided through tax code to motivate particular behavior.

²This paper treats Education IRA (Coverdell) as ESA instead of IRA.

³They are independent cross-sections over 2001, 2004 and 2007. SCF is conducted every three years recently.



(a) (Log) Mean income differences between cohorts with ESA and ESP



(b) Proportions of households with both ESA and ESP at ESA and ESP cohorts

Source: Survey of Consumer Finance (2001, 2004 and 2007). I define 14 cohorts with almost equal size according to the age of household head in 2001 and follow them by age through three cross-sections (the starting year and formation of pseudo panel are chosen to be compatible with the empirical model). The average cohort size is 693 households (unweighted). The statistics are produced by pooling all the three cross-sections at each age cohort.

¹ ESA cohort contains all the households holding education saving accounts within each age cohort. ESP cohort include all the households rank education in the first place for the question about the important reasons for saving within each age cohort.

² Yearly average of $\log(\text{Mean income of households with ESA} / \text{mean income of households with ESP})$ at each age cohort.

Figure 4.1: The deviation of households with ESA and ESP on income and their overlapping by age cohort, 2001-2007

number of choices, six could be picked and ranked by the household. Education is one of reasons. Initially, I only count the respondents who ranks education in the first order.⁴ They are denoted to belong to ESP cohort. Starting 2001, the survey began to ask if the household has a Coverdell or 529 educational account. This is deemed the indicator of ESA ownership. I summarize the discoveries:

1. ESA cohorts are richer than ESP cohorts.
2. With respect to the characteristic of income, ESA and ESP cohorts share most homogeneity when the average age of household head is around 45 to 55 in 2001 (the lowest section of the quadratic fitted line).
3. There are far more households with ESP when holding ESA than the other way around. But this proportion within ESA cohort is still almost below a half.

The first finding implies there are high income households contributing to ESA not mainly due to ESP and/or low income households with ESP though not holding ESA. The former possibility might support the hypothesis that rich household favors ESA mainly due to the incentive of tax-sheltering. Particularly, the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA) reinforces this tendency by establishing the prominence of 529 plans which does not have contribution limit and restriction of child's age at distribution and allow the balance to grow tax-free. The second possibility might be explained by the plausible association between a lower level of financial literacy and low income households.⁵ [Dynarski \(2004\)](#) provides a concrete breakdown on the positive correlation between income and the advantages of the tax-advantaged college savings accounts: first, those with the highest marginal tax rates benefit the most from sheltering income, gaining most in both absolute and relative terms; second, those in the top tax brackets benefit more from non-educational use of ESA than those in the bottom bracket gain from its educational use; finally, the college financial aid system reduces aid for those households that have any financial assets, including an ESA or 529. But the highest-income households are more possibly to be unaffected by this aid tax since their asset level should have been far above the margin. The

⁴In the econometric model, I will also include a broader ESP definition by counting the household which has education as anyone of the six most important reason.

⁵[Case and McPherson \(1986\)](#) investigate parental saving incentives and cite that irrational action can be caused by the lack of awareness about financial aid program. In fact, there is no barrier from tax code to defer the low income households to select ESA if they do have ESP.

other noticeable advantage for rich parents is 529 plan allows the shift of asset to offsprings without triggering estate tax.

The second evidence shows the association of ESP and ESA ownership differs in the life-cycle. The strongest moment happens when the first-born child of the average parents is close to the college age (18 years old) in US. This can be another support for my theoretical postulation in Chapter 2: parents are indeed involved in a finite horizon learning process in financial preparation of college cost which implies more education saving driven by ESP in the end when the college-bound uncertainty is diminishing most intensively.

The last point reveals there are significantly many households not utilizing ESA to fulfill ESP though ESP seems to be one of the main forces in the decision of ESA. And there are much more households with ESP than ESA. These are all the proofs for the mismatch of these two populations.

This chapter concentrates on the empirical questions: is it true ESA contributors bear strong ESP across different income groups? To answer these questions, I turn to a synthetical panel formed from SCF 2001-2007. The estimation is implemented by a GMM approach on the dynamic panel specification to control the unobservable saver heterogeneity and endogeneity. In section 4.2, I describe the data and production of pseudo panel. Section 4.3 presents the strategy to control the saver heterogeneity by forming pseudo panel. Section 4.4 and 4.4.2 explores the model specification and estimation methods. Section 4.5 presents the results. Section 4.6 renders a policy discussion on the empirical outcome. And section 4.7 summarizes this chapter and discusses the limitation.

4.2 Data

This study relies on the Survey of Consumer Finances. This is the only public data containing the information on ESA. And the ESA related questions only appears in the wave of 2001, 2004 and 2007. SCF is a triennial survey of the balance sheet, pension, income, and other demographic characteristics of U.S. households. The study is sponsored by the Federal Reserve

Board in cooperation with the Department of the Treasury. Since 1992, data have been collected by the National Organization for Research at the University of Chicago (NORC). To ensure the representativeness of the study, respondents are selected randomly using procedures with a strong attempt to include households from all economic strata. About 4,500 households are interviewed in every cross-section. Since this study focuses on the education saving for the child, the final sample is restricted only towards the household with positive number of children to avoid ambiguity. To form a synthetic panel, I extract three continuous waves from 2001 to 2007.⁶

In SCF, a multiple imputation procedure yielding five replicates for each missing value is used to approximate the distribution of the missing data. The individual imputation are made by drawing repeatedly from an estimate of the conditional distribution of the data. The imputations are stored as five successive replicates of each data record. Thus, the number of observations in the full data set is five times the actual number of respondents.

Similar to [Gale and Scholz \(1994\)](#), I choose income and wealth as they are important determinants in the college-bound decision as well as standard life-cycle saving model. My wealth measures include financial assets, debt and nonfinancial assets. Nonfinancial assets can reflect the initial wealth level. Higher initial wealth encourages more consumption and thus reduces any sort of saving. But controlling for other factors, differences in asset holdings may be correlated with tastes of savings. Therefore, the predicted effect of assets on saving is ambiguous. The role of debt is also uncertain in deciding saving behavior. If rich households are taking advantage of the easy credit and low interest, e.g., the prevalent application of second line of credit/mortgage during the data period (2001-2007), there might be a positive relationship since more residual wealth is available. But the concern of debt reimbursements makes ESAs less attractive due to its low liquidity.

The other demographic variables include the number of children, marital status, and education of household. It is plausible to expect a positive relationship between a married people with more children to bear more ESP, though large household size will require more impending expenditure supported by holdings on liquid asset instead of ESAs. More educated parents may be more financially sophisticated and can thus access ESAs with less transaction cost. Saving tastes, e.g., time preference, may also be correlated with education. Either case would predict that more educated household heads would have more chances to hold ESA. A bequest motive variable is included to capture

⁶The sample size are 9,685, 9,955 and 9,740 respectively for 2001, 2004 and 2007 (these are almost five times original raw sample due to multiple imputation, which is discussed shortly). Since the estimation is based on a dynamic panel specification.

the psychological/economic measure of children's future value which plays the role in determining their college-bound saving decision too.⁷

[insert Table 4.1]

Table 4.1 shows the characteristics of households with child in terms of the ownership of ESA and ESP and provides the description of variables.⁸ Married people with higher ESP, higher education level, more children, income and debt will be more likely to hold ESA. The pattern of these variables for ESP ownership is similar to ESA's. However, ESP cohort has relatively more single household heads. Their education and income levels are also relatively lower. And the exposure to the debt is less severe. ESP cohort exhibits the reverse pattern due to ownership over the rest of variables. Namely, there are more single and younger household heads bearing ESP than ESA. They can be the single mothers/fathers which are too poor to establish ESA. They also drag down the median financial assets of ESP cohorts. It is interesting to observe ESP cohort has stronger bequest motive than non-ESP one, which is totally opposite for the ESA counterpart. This might imply there are many less educated parents emphasizing on the child's future and intensively expecting the improvement of offspring's social/education status. But they have difficulties and/or unwillingness to access ESA. Instead, ESA holders might bear the strategic thinking which uses the ESA contribution to incentivize the child's scholastic activity but displaying less bequest motive in order to avoid the free-riding from the child. This table also includes pension and IRA dummy. [Poterba et al. \(1994, 1995\)](#) treats pension ownership as a signal of saving taste due to personal preferences or better job stability. [Ma \(2003\)](#) regards IRA as a good signal for household's familiarity with other tax-favored instruments such as ESA. Obviously, we have evidences that ESA is chosen more by these two reasons than ESP itself from this table.

Lastly, I count in two additional dummies: borrowing to finance education and education expenditure foreseeable. The former is one if the respondent answers yes to the question: "it is all right for someone like yourself to borrow money?" These group of parents might not worry much on education saving. A typical scenario in the recent decades is that buyers of housing in good school district also have more access to home equity loan. A great number of them do use it to finance education. Since they are living in the good school district and holding better projection towards child's college prospect, they tend to lower their ESP and also propensity to save via ESA. However, other

⁷[Gale and Scholz \(1994\)](#) pointed out the relationship among intergenerational transfer, saving and bequest behaviors.

⁸Definition of ESA and ESP has been presented in Section 4.1.

possibilities also exist. As discussed, rich households might utilize the easy credit to increase asset accumulation. Poorer ones instead might treat the borrowing opportunity simply as a substitute of saving. The direct inference from the Table 4.1 favors the complementarity interpretation for both ESA and ESP cohorts. The dummy of education expenditure foreseeable is one if the respondent answers his/her family expects to have to pay for themselves the foreseeable educational expenses in the next five to ten years. I include this one to reduce the measurement error of self-reported ESP variable. It is unsurprising that both ESA and ESP owners show more probability to really have to bear the burden in the future.

4.3 Estimation strategy

Household education saving tastes may vary because of unobservable individual specifics. For example, the far-sighted parents would have obtained higher education level and prefer to encourage the child to pursue higher education than others. In result, they tend to bear more ESP. These parents are also more likely to choose ESA since they are richer to enjoy more tax benefit and more financial literate about it. Without taming this heterogeneity, the model would overestimate the linkage between ESA on ESP.

Gale and Scholz (1994) and Venti and Wise (1992, 1995) use real panel to control the unobserved individual specific when estimating the effect of IRA on net savings. Poterba et al. (1995) estimate the similar offsetting effect from 401(K) by the exogenous identification from its eligibility status. Due to the data limitation and lack of eligibility condition for ESA, I rely on the method of pseudo panel to control for saver heterogeneity. Similar approach appears in Poterba et al. (1995) and Engen and Gale (1997) which group the observations by the same demographics, income and participation status of 401(K) or IRA in an effort to differentiate out the fixed effect.

For the formation of synthetic panel, we have to take enough care of the measurement error. A higher number of observation in each panel can introduce more variation to curb down the bias from measurement error. On the

other hand we prefer to make as many panels as we can to better control the heterogeneity. Consequently, there is a trade-off regarding the number of observations per cohort (Benitez-Silva and Bae 2005; Collado 1997). As Deaton (1985) suggested, 150 observations per panel can be asymptotically appropriate to approximate the cohort population mean by sample counterpart.⁹

My grouping condition is age since the association of ESA and ESP bears life-cycle features as shown in Figure 4.1(b). I thus cut the sample by the age of household head in 2001. Totally there are 53 age cohorts and 159 cells (58×3). They are then followed in every next cross sections (2004 and 2007) by shifting the minimum and maximum age for each cohort by every three years sequentially.¹⁰ The average cell size is 183.

4.4 Empirical model

4.4.1 Specification

The model to be estimated is:

$$\begin{aligned}
 ESA_{it} = & \alpha + \delta ESA_{it-1} + \eta' x_{it} + \gamma_1 \times Lowinc_{it} + \gamma_2 \times Highinc_{it} \\
 & + \beta_1 \cdot ESP_{it} + \beta_2 \cdot ESP_{it} \times Lowinc_{it} + \beta_3 \cdot ESP_{it} \times Highinc_{it} + v_{it},
 \end{aligned}
 \tag{4.1}$$

where $v_{it} = \lambda_t + \mu_i + \varepsilon_{it}$, $i = 1 \dots N$ and $t = 1 \dots T$.

ESA_{it} is the average balance in ESA for cohort i , at time t . x_{it} is the vector of cohort means of the controls as discussed in Section 4.3. They include single dummy, number of children, years of education, bequest dummy, pension dummy, IRA dummy, financial assets, debts, nonfinancial assets. There is a variable denoting the income percentile group each observation belongs

⁹Also see Vilaplana et al. (2006).

¹⁰For instance, the first cohort contains all the households with the head's age between 18 and 19 years old in 2001, 21 and 22 years old in 2004, 24 and 25 years old in 2007. They are very likely different households.

to at each cross-section in SCF, which has six groups. Here are the group order id and percentiles each covers: 1 = 0-20, 2 = 20-39.9, 3= 40-59.9, 4 = 60-79.9, 5 = 80-89.9 and 6 = 90-100. From them, I extract the income percentiles which have accounted for the weighting by design. If the median income of cohort i at period t is below 40th percentile (i.e., it belongs to income percentile group one or two), this cohort is considered to be low income group with the dummy $Lowinc_{it} = 1$.¹¹ If the median income of cohort i at period t is above 80th percentile (i.e., it belongs to income percentile group five or six), this cohort is considered to be high income group with the dummy $Highinc_{it} = 1$. Otherwise, it is considered to be median income group with both dummies to be zero. This method of assigning income group can accurately locate each cohort's income status considering the skewness of income distribution. Finally, within the error term v_{it} , λ_t is a year-specific dummy, μ_i is the unobservable cohort-specific with zero mean and ε_{it} is the disturbance term. It is assumed that ε_{it} is independently distributed across cohorts with zero mean, but heteroscedasticity across cohorts and time is allowed.

Two ESP measures are incorporated. Initially, ESP_{it} is the proportion of households which rank education in the first order among the six most important reasons for saving. The other ESP measure allows ESP_{it} to be the proportion of households which present education in any of the six most important reasons for saving. The answer to the central question raised in Section 4.1 lies in the coefficients β_k , $k = 1, 2$ and 3. The effect of using ESA to fulfill ESP from the median-income group is shown by β_1 . And the total effect of ESA on the low-income and high-income groups are represented by $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$, respectively.

The dynamic panel specification is based on two aspects of justification:

Saving inertia can arise from consumption habits, smoothing and particularly the learning process central in this dissertation.¹² As discussed in Chapter 3, ESP in every period should depend on the lagged one which contains mainly the information of prior on the child's ability.

On the other hand, we can deem our central question instead to be the relationship between optimal demand of education saving (ESA_{it}^*) and ownership of ESA. ESA_{it}^* can be specified to be:

$$ESA_{it}^* = \alpha + \tilde{\eta}' \tilde{x}_{it} + \tilde{v}_{it}, \quad (4.2)$$

where \tilde{x}_{it} includes everything except α , ESA_{it-1} and v_{it} and \tilde{v}_{it} is similarly

¹¹The cutoff point for low income group cannot be too low to bear any tax liability. Otherwise, ESA is almost meaningless for low income household.

¹²The seminal work from Hall (1978) shows, with a quadratic utility function, saving will be AR(1) if income follows an AR(1) process.

a composite error term. in 4.1. Nerlove (1958) systematically proposes the structural foundation for the generation of lagged dependent variable by introducing partial adjustment hypothesis: if we postulate our cohort proportion of ESP ESA_{it} is a linear approximation of the actual demand of education saving, the adjustment towards equilibrium can be stated as

$$ESA_{it} - ESA_{it-1} = \gamma(ESA_{it}^* - ESA_{it-1}), \quad (4.3)$$

where γ measures the rate of adjustment such that $\gamma \in (0, 1]$. In this sense, plausibly we consider that the actual change of demand in education saving is proportional to the optimal change. Combination of 4.2 and 4.3 creates 4.1 after rescaling the coefficients.

4.4.2 Estimation method

When lagged dependent variables are present, both the traditional within groups and the random effects estimators are biased and inconsistent unless the number of time periods is large (tends towards infinity).¹³ Again, I adopt the preferred estimator ‘system GMM’, a Generalized Method of Moments (GMM) estimator suggested by Arellano and Bover (1995) and Blundell and Bond (1998). This GMM estimator is consistent with relatively small T but big N such as the pseudo panel here. Furthermore, other concerns on endogeneity can be tackled by this estimator. Some of the explanatory variables can be jointly determined with ESP variable ESA_{it} . For example, ESA contribution is strongly determined whether the household values education saving. Additionally, many regressors can be correlated with the unobservable cohort-specific because it bears the saving taste which also interacts with parents’ education level, bequest motive and so on.

‘System GMM’ is an improvement based on ‘difference GMM’. The latter is proposed by Arellano and Bond (1991) to take first differences to remove the fixed effect μ_i and instrument the differenced model by lagged levels of w_{it} : ΔESA_{it} is instrumented by $ESA_{i0}, ESA_{i2} \dots ESA_{it-2}$. However, if the dependent variable almost follows a random walk, there is finite-sample bias of ‘difference GMM’ (Blundell and Bond 1998; Roodman 2006). ‘System GMM’ provides a more efficient solution by adding extra moment conditions for the equations in levels:

$$E[\Delta w_{it-1}(\mu_i + \varepsilon_{it})] = 0, \quad (4.4)$$

where w_{it-1} includes all the instruments which can be the dependent variable and regressors. The additional assumptions require $E[\Delta w_{it-1}\mu_i] = 0$ and ε_{it}

¹³Refer to the discussion in Section 3.3.2 and Baltagi and Boozer (2009).

is not serially correlated. Arellano-Bond and Sargan tests are common for the verification of these two assumptions. [Arellano and Bond \(1991\)](#) proposes the test statistics for presence of serial correlation in the first differenced residuals of first and second order, respectively. The checking always relies only on the second order test because the significant negative AR(1) is always expected by design. The [Sargan \(1958\)](#) test statistic of overidentifying restrictions is χ^2 -distributed with degrees of freedom equal to the number of instruments minus the number of estimated parameters. This misspecification test does not indicate correlation between the instruments and the error term.

To account for MA(1) process in $\Delta \varepsilon_{it}$ from the differenced equations as well as more general heteroskedasticity, two-step estimation is chosen. The first-step estimator adopts a weighting matrix which handles MA(1) process with coefficient -1 in $\Delta \varepsilon_{it}$. Next, a robust clustered GMM weighting matrix is derived from the estimated residuals from first-step result in an effort to achieve higher efficiency.

Besides, if some explanatory variables are predetermined, the contemporaneous difference is also valid instrument.¹⁴ Therefore, we can include more moment conditions by determining whether some variables are predetermined. Starting out by treating all but lagged dependent variable as predetermined variables, estimation experiments by shifting some explanatory variables to be endogenous until enough t-values and specification tests render satisfying outcomes.

4.5 Results

Table [4.2](#) presents the estimation results when two measures of ESP are considered.

[insert Table [4.2](#)]

¹⁴They are correlated with past realization of disturbances instead of the current or future ones.

Column [1] shows the estimate with initially stricter measure of ESP. Almost all the coefficients are significant except those for low income dummy, single dummy, education and IRA dummy. The effect of lagged dependent variable is positive which reveals it might be subject to an adjustment process as implied by (4.3) ($\delta = 1 - \gamma$). β_1 shows ESA contribution is inversely related with ESP among median income households. However, relative to them, low income and high income households contributes more ESA since β_2 and β_3 are positive. More stable and richer households should be more likely to hold pension. Likewise, data suggest their contribution to ESA significantly rises by the similar reason. As expected, singles tend to hold less ESA although the result is insignificant. Number of children does significantly increases the propensity to contribute more on ESA. Education of household head is surprising negatively related with ESA contribution. But it is not significant. Less educated parents could be more demanding for their child's education which arise as the foremost important reason to save. This line also goes towards the explanation on the negative effect from financial asset. Significant pension dummy supports the hypothesis on the positive impact from job security. The negative coefficient of IRA dummy illustrates the crowding out effect though it is highly insignificant. Parents in strong demand of education saving would choose to transfer fund from IRA to ESA. Significantly positive effect from bequest motive variable reinforces the postulation on strategic saving behavior. The households with better endowment should hold more nonfinancial assets and tend to be more far-sighted to plan well on child's future education. This explains the significantly positive coefficient before nonfinancial assets. The highly significantly negative impact from the attitude of borrowing to finance education might follow from the prevailing argument that easy credit crowds out saving even if it is tax-favored. Household with education expenditure foreseeable is undoubtedly more likely to contribute on ESA as suggested by the significantly positive coefficient.

When the less strict measure of ESP is included, column [2] presents the results. The magnitude and significance of most coefficients improve and the signs are unchanged, especially those over the income status dummies and the joint terms with ESP measure. This assures that the model specification is robust.

To implement second order Arellano and Bond autocorrelation test, we need to establish the differenced equation up to at least two periods of lags which is unavailable since $T=3$ in this data. Therefore, the only autocorrelation test available is the alternative Arellano and Bond AR(1) tests for the level equations instead. The outcomes are shown under Table 4.2 along with the Sargan test. Both of them do not indicate misspecification.

I investigate the heterogeneity of ESP effect due to income difference through a number of Wald tests. They are provided at the bottom of Table 4.2 as two groups. The first group attempts to reveal the overall association of ESA and ESP for low income and high income households respectively: $H_0: \beta_1 + \beta_2 = 0$ and $H_0: \beta_1 + \beta_3 = 0$. The results for the strict ESP measure are $F(1, 52) = 3.11$ with $\text{Pr} > F = 0.084$ and $F(1, 52) = 0.45$ with $\text{Pr} > F = 0.504$ respectively. This states the low income households do contribute more on ESA when their ESP rises. But it is not evident for the high income households. The counterparts for the less strict ESP measure are $F(1, 52) = 5.43$ with $\text{Pr} > F = 0.024$ and $F(1, 52) = 3.72$ with $\text{Pr} > F = 0.059$ respectively. High income households turn to ESA more intensively only when their ESP is not quite strong. Therefore, parents do resort to ESA whenever there is motive for education saving. But the result is more significant for low income group. The conclusion is that the marginal effect of ESP on ESA contribution is relatively more prominent for the low income group.

The next group of tests reveals the marginal effects of income on ESA contribution when income status switches from median to low and this changes from median to high: $H_0: \gamma_1 + \beta_2 \times \overline{ESP} = 0$ and $H_0: \gamma_2 + \beta_3 \times \overline{ESP} = 0$. The results for the strict ESP measure are $F(1, 52) = 0.07$ with $\text{Pr} > F = 0.797$ and $F(1, 52) = 8.88$ with $\text{Pr} > F = 0.004$. The counterparts from the less strict ESP measure are $F(1, 52) = 0.19$ with $\text{Pr} > F = 0.664$ and $F(1, 52) = 16.55$ with $\text{Pr} > F = 0.0002$. Both show that contribution rises with income level. But the previous group of tests assures that this increase cannot mainly origin from the line of ESP. In result, the established argument that ESA functions more effectively as a tax-shelter can be quite reasonable.

4.6 Policy implication

The section presents a policy discussion on the empirical findings on ESA by extracting the insights from my main saving with learning model.

4.6.1 Inefficiency of tax-preferred ESA to encourage ESP

Our GMM estimator finds that families contributing to ESA mismatch with those with ESP: the contribution of ESA cannot be fully explained by the ESP, which is more serious among median and high income groups. This actually supports the arguments on the regressive feature of ESA introduced by state and federal government, e.g. 529 plan and Coverdell Education Savings Account (Dynarski 2004; Ma 2003): ESA is mainly the other tax sheltering tool used by the rich and does not stimulate saving from households which have high propensities to use it for educational purpose.

Since the benefit of ESA such as 529 is conditional on the final college enrollment decision, this actually reduces the marginal wealth effect. If child does not enter college, all the distributions can not be qualified educational expenses to enjoy the waive of income tax. Plus, a penalty (now 10%) will be imposed on these distributions. More or less, the benefit can be considered as a one-time tuition subsidy and reduce the gap of asset positions between the binary state of college-bound choice. Therefore, $\bar{\theta}$ drops and becomes flatter with asset. The absolute value of option increases but the marginal one with respect to wealth decreases. The former effect might intrigue some incumbents to start opening an ESA but the latter effect influencing the existing holders of ESA could be uncertain, which depends on the combinational states of parents' asset and prior. This follows from my model prediction and is confirmed by the empirical model in this chapter.¹⁵ However, those very optimistic or pessimistic will be very likely to contribute less.¹⁶ As a result, these parents would shift saving out of ESA to other forms to maintain higher option value. This also sheds the light on the reason why ESA cannot capture enough propensity to save for college. In reality, the population of highly optimistic and/or pessimistic parents can be quite large when not enough intra-family interaction is involved. On the other hand, for relatively optimistic parents, the one-time increase in absolute option value might intrigue higher level of oversaving, which has negative impact on their welfare.

4.6.2 Policy suggestion

As the discussion follows, the pecuniary benefit introduced by simply changing option value of college saving conditional on final college enrollment might

¹⁵The overall association between ESA and ESP is significantly non-positive for median and high income group.

¹⁶Their marginal effect of wealth on option value of college choice may very possibly decrease (see equation (2.10)) since the change of $\bar{\theta}'$ should dominate and that of $F_c(\bar{\theta})$ is neglectable.

not lead to satisfactory outcome, particularly when parents are highly uncertain of child's ability. This study shows encouraging early acquisition of child's ability information can better off the linkage between wealth effect, such as tax benefit, and college saving. Thus, the college participation can be much better prepared financially among parents who are either pessimistic or poor. Plus, there is evidence of positive psychological and behavioral effects of savings on educational achievement. (Destin and Oyserman 2009; Elliott 2009).

ESA policy providing incentive to learn child's ability early can be an effective way to capture more motive to save for college via ESA when they are combined. There are two methods already introduced across the states:

- Partnership between GEAR UP and ESA (Clancy and Miller 2009): Gaining Early Awareness and Readiness for Undergraduate Programs (GEAR UP) was established in the Higher Education Amendments of 1998 to increase the low-income family students' and parents' readiness, selection and funding for accessing higher education. In addition to making college more accessible financially, GEAR UP scholarships reward parents involvement so that they can know child's prospect better and early since GEAR UP starts serving the students no later than the seventh grade. State's partnership programs matches deposits in 529 savings accounts with federally-funded GEAR UP scholarships to induce the parents' learning.
- Multiple states have already provided matching contributions.¹⁷ This actually distribute the value of option across years and lowers the startup requirement for college saving. Therefore, parents are more likely to be induced to start college saving even with a very low level. The spread of option value encourages them to gauge the decision whether to take the match every next year sequentially based on child's ability signal since the exit or entry cost at every period is lower. Additionally, the earlier contribution means more matching. Parents would tend to begin the contribution earlier and thus learn the child earlier.¹⁸

The other possible approach is to apply a regressive tax benefit in terms of time, which intends to reward much earlier contributions and punish the later ones. Currently, 529 plans have contributions grow tax-free over time. Instead, for instance, the benefit enjoyed by contributions close to child's col-

¹⁷For example, Arkansas, Oklahoma, Colorado, Maine, Michigan, Nebraska and Alabama. The amount ranges from \$200–\$500 per year.(see http://www.savingforcollege.com/compare_529_plans/)

¹⁸This analysis shares the idea similar to that in the *Learning Effect IV*.

lege enrollment age might be discounted back to those earlier contributions (namely, matching them).¹⁹

4.7 Conclusion

This chapter is the first attempt to explore the relationship between ESA and ESP by using a formal econometrical model and nationwide dataset.²⁰ We can confirm the overall economic efficiency of current tax policy on education saving across all the income levels: parents contributing to ESA do bear education saving propensity. This is exceptionally prominent among low income households though not significant among richer ones. Thus, we may argue that ESAs, as the other tax-favored instrument, may be similar to IRAs in the perspective of tax-sheltering. The complementarity between IRA/pension and ESA decisions can be the evidence. My saving with learning model renders the interpretation on the economic inefficiency of ESA by exposing the inappropriateness of its incentive structure when uncertainty on child's ability is present.

SCF is the only data which contains information about ESA selection. Since the introduction of this policy starts only within one decade, we don't expect the information of ESA has been well spread.²¹ The other limitation is there are only three waves of samples providing response regarding ESA. It is also more realistic to incorporate the other valuable considerations such as projection of college expenditure, education loans and financial aid. These await future research. All of these barriers and expectation await to be solved and achieved.

¹⁹The other effect involved is to curb down oversaving. Given a fully estimated model, I can carry out some experiments to examine the validity of these policy proposals. This will be the extension in the next step.

²⁰Dynarski (2004) does not develop an econometric model and the results from TIAA-CREF survey in Ma (2003) may not be appropriately extended to the whole population.

²¹The approximate proportion of sample, for instance in year 2004, choosing ESAs is only 4%.

Table 4.1: Characteristics of households with child by the ownership of ESAs and ESPs, 2001-2007

Variables ¹	ESA ownership		ESP ownership		Total
	No	Yes	No	Yes	
Percentage with ESP	19.9	29.8	-	-	20.4
Percentage with ESA	-	-	4.1	6.7	2.4
Average ESA balance \$	0	38,329	1,736	1,872	1,764
Average age	42.6	42.9	43.6	38.7	42.6
Percentage single	28.1	13.7	28.0	25.4	27.5
Average no of children	1.9	2.0	1.8	2.1	1.9
Average (years) education	13.1	15.6	13.2	13.3	13.2
Percentage with pension	58.0	80.3	59.5	56.9	59.0
Percentage with IRA	25.8	69.5	28.4	25.6	27.8
Average bequest motive	2.7	2.8	2.7	2.6	2.7
Median income \$	54,219	124,433	56,525	57,608	56,525
Median financial assets \$	14,976	212,706	19,000	14,075	18,000
Median debt \$	57,400	163,800	60,500	70,200	63,180
Median nonfinancial assets \$	143,990	376,000	155,727	145,310	154,000
Borr. to finance edu. %	87.0	92.4	86.0	92.0	87.3
Edu exp. foreseeable %	38.7	57.6	35.8	54.2	39.5

Source: Survey of Consumer Finance (2001, 2004 and 2007). Data are weighted to represent the whole population across these three years. All of the dollar measures are converted to 2007's value. The weighted sample size: without ESA - 138,620,888; with ESA - 6,687,638; without ESP - 115,721,231; with ESP - 29,587,295; total - 145,308,525 (note that they are the sum of the three years' samples).

¹ Pension dummy =1 if it exists for either head of household or partner from a current or past jobs; IRA dummy =1 if head of household or any other household member has any Keoghs or IRAs; bequest motive is an ordered variable about the feeling from head of household or partner on the importance to leave an estate or inheritance to their surviving heirs. It ranks from one(very important) to five(not important); financial assets consist of liquid assets, certificates of deposit, directly held pooled investment funds, stocks, bonds, quasi-liquid assets, savings bonds, whole life insurance, other managed assets, and other financial assets; debt includes principal residence debt (mortgages and home equity line of credits), other lines of credit, debt for other residential property, credit card debt, installment loans, and other debt; nonfinancial assets cover all vehicles, value of primary residence, value of other residential real estate, net equity in nonresidential real estate, value of business interests, and other financial assets. See definitions of these terms for further details; borrowing to finance education dummy = 1 if the respondent answers yes to the question: "it is all right for someone like yourself to borrow money?"; education expenditure foreseeable dummy = 1 if the respondent answers his/her family expects to have to pay for themselves the foreseeable educational expenses in the next five to ten years.

Table 4.2: GMM estimate for the association between ESP and the contribution to ESA

Variable	[1] ^a		[2] ^b	
	Coeff.	(SE)	Coeff.	(SE)
ESA balance $[t - 1]$: δ	0.243***	(0.061)	0.185**	(0.087)
ESP: β_1	-2.169	(1.369)	-3.728**	(1.571)
Low income \times ESP: β_2	3.603**	(1.525)	5.531***	(1.735)
High income \times ESP: β_3	3.307*	(1.913)	5.915***	(2.043)
Low income: γ_1	-0.525	(0.395)	-1.377*	(0.796)
High income: γ_2	-1.233***	(0.312)	-2.336***	(0.391)
Single	-0.531	(0.540)	0.314	(0.572)
No. of children	0.425**	(0.201)	0.767***	(0.254)
Education	-0.070	(0.060)	0.006	(0.073)
Pension dummy	2.525***	(0.566)	3.796***	(0.546)
IRA dummy	-0.190	(0.690)	0.140	(0.818)
Bequest motive	0.345**	(0.132)	0.303*	(0.154)
Financial assets	-0.001**	(0.000)	-0.001	(0.000)
Debt	0.003*	(0.001)	-0.001	(0.001)
Nonfinancial assets	0.0003***	(0.0001)	0.0004***	(0.00006)
Borrowing to finance education	-3.811***	(0.566)	-3.233***	(0.492)
Edu expenditure foreseeable	0.864**	(0.398)	0.676	(0.601)
Wald tests	F(1,52)	Pr > F	F(1,52)	Pr > F
$H_0: \beta_1 + \beta_2 = 0$	3.11	0.084	5.43	0.024
$H_0: \beta_1 + \beta_3 = 0$	0.45	0.504	3.72	0.059
$H_0: \gamma_1 + \beta_2 \times \overline{ESP} = 0$	0.07	0.797	0.19	0.664
$H_0: \gamma_2 + \beta_3 \times \overline{ESP} = 0$	8.88	0.004	16.55	0.0002

Source: Heteroskedasticity consistent standard errors are reported in parentheses. Significance level: *** 1%, ** 5% and * 10%. Both time dummies and a constant are included. After experimenting, the classification of instruments is: the endogenous variables are ESP proxy $[t - 1]$, ESA, Lowinc \times ESA, Highinc \times ESA, education, bequest motive, the predetermined ones are Lowinc, Highinc, IRA dummy, pension dummy, no. of children, single, financial assets, debt and nonfinancial assets, and the strictly exogenous one is time dummies.

^a ESP measure covers only the parents who rank education in the first order among the six most important reasons to save. For [1], Arellano and Bond autocorrelation tests for the level equations: $z = -0.45$ Pr > $z = 0.651$ for AR(1) test. The Sargan test shows $\chi^2(35) = 97.34$ and Pr > $\chi^2 = 0.000$.

^b ESP measure covers all the parents who select education no matter what order is in the six most important reasons to save. For [2], Arellano and Bond autocorrelation tests for the level equations: $z = 0.15$ Pr > $z = 0.884$ for AR(1) test. The Sargan test shows $\chi^2(35) = 86.80$ and Pr > $\chi^2 = 0.000$.

Chapter 5

Summary

This study formally pins down the main risk involved with college saving and introduce the important behavioral factor such as confidence in saving model.¹ Data suggest pessimistic and/or rich parents reduce the education saving, the state dependence of parents' college expectation and diminishing persistence over time due to learning.

This dissertation provides the explanation on the findings that the present education saving plans are inefficient to capture the saving propensity for college. My model suggests a couple of fiscal policies on education saving which encourage more parents-child interaction to improve the learning of child's ability.

The model presented in this paper can also be extended to researches on career choice, entrepreneur behavior, and portfolio choice with learning, when agent is confronted with the tradeoff between intertemporal substitution and a real option. Two particular applications I am interested in are:

- The dependence of learning on physical constraint can be applied to issue such as optimal investment in R&D with information acquisition involved. A typical example is the decision about when and how much to prepare for the future patent fee (or other kind of entry cost) for a new drug under development, whose quality can be accessed by learning. At the same time, the manager is also confronted with financial or capacity

¹There are also uncertainties on tuition level and financial aid which play roles in parents' investment in child's higher education. The model developed under current stage only captures the main uncertainties on ability. Besides, college enrollment is not only an endogenous decision but also dependent on the exogenous college eligibility controlled by admission offices. The latter bears the uncertainty too. All of these risks might be considered in the future extension. [Browning and Lusardi \(1996\)](#) and [Keane and Wolpin \(2001\)](#) suggest the significance to account for a whole range of behavioral issues beyond consumption and saving decisions.

constraint as well as intertemporal choice of asset allocation.

- This model introduces saving in learning and search/real option framework. A particular heated extension is to add intertemporal choice and wealth effect on the issue of learning and climate change (O'Neill et al. 2006). O'Neill and Sanderson (2008) investigates the implications of the learning potential on population growth for mitigation costs of emission reduction and optimal emissions since population size is the main determinant of emission. But the model is lack of intertemporal choice and wealth effect, which might be naturally imbedded when fossil fuel consumption, tradable carbon credits as well as asset/resource stocks are considered.² I hope this extension might shed a light on why developed countries are so reluctant to embrace Kyoto Protocol by the implication from the current model. Furthermore, my model suggests more “Inconvenient Truth” might be a solution.³

Further empirical evidence of the wealth effect on the option value and college saving and a structural estimation will be sought in the next step in order to shed more light on policy research involved with college saving.

²Wirl (2006) established a model concerning intertemporal choice of the carbon tax (or equivalently, use of fossil fuels) and optimal timing of either temporary or irreversible abandonment of fossil fuels.

³This derives from the *Learning Effect IV*.

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Appendix A

Data description

This appendix covers the variable constructions in the samples from NELS88 and PSID/CDS & TA.

A.1 Variables from NELS88

I draw the empirical evidence from National Education Longitudinal Study of 1988 (NELS88) to expose unique features on saving for college. In this survey, a nationally representative sample of eighth-graders were first surveyed in the spring of 1988. A subsample of these respondents were then resurveyed through four follow-ups in 1990, 1992, 1994, and 2000. 3,703 respondents (with their parents) are included who do not have missing values in questions about college saving and cognitive test scores when they are at 8th and 12th grade.

The questionnaire contains a question on how much parents have saved for child's future college education for two waves when child is at 8th and 12th grade (Ingels 1994b). The college saving categories are obtained from the question: "money respondent set aside for child's future education", asked when the child is at 8th and 12th grades. The parents do not confront with this question if they answered "No" in the other two screening questions appearing before this college saving question by the following orders:

1. “do you expect that your eighth grader will go on to additional education beyond high school?” (at the wave of 8th grader); “does teen plan to continue education?” (at the wave of 12th grader)
2. “have you or your spouse/partner done anything specific in order to have some money for your eighth grader’s education after high school?” (at the wave of 8th grader); “grade teen in when respondent started saving” (at the wave of 12th grader; “Not Begun” is the choice in this question corresponding to “No” in others.)

Similar to CDS, this structure assures parents have seriously considered the child’s college-bound chance (e.g. by measuring her ability) and actual financial actions before answering the level of college saving.

This data maintains a nationwide cognitive test on multiple disciplines administered and standardized over all the student respondents who are still enrolled, which is by design highly comparable across waves. There is also a quartile measure for each wave, which I take to decide which half of sample the child’s standardized test score is in. ([Ingels 1994a](#)).

A.2 Variables from PSID/CDS & TA

A.2.1 Asset/income

Household asset information is drawn from the wealth supplement of PSID’s family data. It contains household net worth of wealth by summing separate values for a business, checking or savings, real estate, stocks and mutual funds, and other assets and subtracting out credit card and other debt. Both the value with and without home equity are available and used in this study. Since the wealth supplement is not collected each year, I pick the values closest to the end of each wave of CDS & TA data because this research focuses on the saving behavior of parents after observing the child ability signal. Therefore, the years of asset measures from first to last waves are 1999, 2003 and 2005

respectively. Additionally, wave zero corresponds to 1994 when the last wealth supplement interview occurred before CDS-I (1997).

Total income is a continuous variable in the PSID summing total household income from the previous tax year including all taxable income, transfer income, and Social Security income for anyone in the household. Since PSID is collected every two years recently, I also have to form the values representing the year closest to end of each wave of CDS & TA data. To account for the well-documented measurement error issue in income data, I apply the averaging approach. The timing strategy is consequently formed: the average of 1996 and 1998 for wave one, the average of 2000, 2002 and 2004 for wave two and the average of 2002 and 2004 for wave three.

Finally, all of these values and other dollar measures in this study are converted to 1997's value.

A.2.2 Signal of child's cognitive ability

Childs cognitive ability, conceived broadly to include language skills, literacy, and problem-solving skills, was assessed in CDS-I/II through the W-J Achievement Test C Revised ([Woodcock and Johnson 1989](#)). Two age-standardized scores jointly available in both wave of data are used: Applied Problems (AP) and Broad Reading (BR). The former is a proxy of child's math skill and the latter covers her capacity and mastery of passage comprehension and letter-word ([Mainieri 2006](#)).

This study produces a normalized assessment score for each wave. First two waves of this score are calculated from AP and BR scores from W-J Achievement Tests. I firstly use the age normalized scores of these two test available from data. Then, I form a random sample by dropping the observations from over-sampled low-income/black families in each wave of CDS sample. For comparison purpose, I re-normalize the scores by subtracting the mean and dividing by the standard deviation from the random sample. This re-normalized score has a mean of zero and standard deviation of one for the random sample of respondent. The average of the normalized AP and BR scores is then re-normalize by the same method within the random sample to achieve the final normalized assessment scores. The last wave of score is calculated from high school GPA. The relative scale measure is firstly obtained through dividing raw score by highest GPA in the high school of respondent. I apply the same random sample selection and re-normalization approach again on this scale measure to create the normalized assessment score of wave 3.

A.2.3 College expectation/outcome

This is a binary variable with one (or yes, holding college expectation or entering college) or zero (or no, abandoning college expectation or not entering college). Parent expectations for children attending college are constructed from the question asking heads of households in the CDS how much schooling they expected their child to complete. Response categories included: (1) eleventh grade or less (2) graduate from high school (3) post-high school vocational training, (4) some college (5) graduate from a two-year college, (6) graduate from a four-year college, (7) master’s degree, or (8) MD, LAW, PhD, or other doctoral degree. The reference group with college expectation equal to one consists of parents who responded by selecting numbers 4, 5, 6, 7, or 8. In CDS-II, the question for college expectation is: “Sometimes children do not get as much education as we would like. How much schooling do you expect that CHILD will really complete?” And parents were asked a screening question before this one: “In the best of all worlds, how much schooling would you like CHILD to complete?” From this context, we have reason to believe the college expectation question actually capture the parents’ serious choice of child’s college-bound preparation instead of only aspiration for college after taking all the constraints, *e.g.* child’s ability and family financial situation, into account.¹

College outcome information is collected from TA questionnaire, which asked whether respondent ever attended college.

A.2.4 Others from PSID/CDS & TA

Urbanicity is measured by Beale-Ross Rural-Urban Continuum Code for residence at the time of the each interview (Mainieri 2006). These codes are based on matches to the FIPS state and county codes, which range from 1/most urban to 10/most rural.

Child’s behavior problem index (BPI) is drawn from CDS-I. Higher score on this measure implies a greater level of behavior problems.

¹The college expectation question in CDS-I is “How much schooling do you expect that (CHILD) will complete?” There was no screening question before this one. The parents’ college expectation for child should be same as their aspiration considering CDS-I interviewed at an early stage of child’s development when none of them had started high school.

A.2.5 Yearly college expenditure from NCES

The NCES Digest of Education Statistics provides state-by-state data on college attendance and tuition. These data are used to determine the probability that a freshman attends three types of college based on his state of residence: four-year public, two-year public and four-year private in 1997, 2003 and 2005. Additionally, the average yearly college expenditure for these three types of college in a specific state is also drawn from these data for these three years. This expenditure covers undergraduate tuition, fees, room, and board charged for full-time students. Each child's yearly college expenditure expected by the parents in each wave is a function of four variables: the probability of attendance in each type of college, average yearly college expenditure for each type of college, state of residence and year of each wave.

Appendix B

Numerical algorithm

1. Setting:

- Assets - $A(i, t)$: gridpoint, $i = 1..N_a(t)$. Let $A(1, t) = B_t^C$, since this study is concerned with the area there is ability threshold and blue-state value function can be evaluated by analytical expression. $N_a(0)$ can be assigned arbitrarily. Then, $N_a(t + 1)$ is determined such that the range between $A(1, t)$ and $(A(1, t) + I(t))R$ contains required number of grids for enough refinement purpose.
- Ability - $m(j)$: gridpoint, $j = 1..N_m$. The end points represent lower and upper bound. $\Delta_m = \frac{m(N_m) - m(1)}{N_m}$
- Discretized markov transition probability:
$$f(p, q, t) = \frac{\Phi\left(\frac{m(p) + \Delta_m/2 - m(q)}{\sigma_{t-1}}\right) - \Phi\left(\frac{m(p) - \Delta_m/2 - m(q)}{\sigma_{t-1}}\right)}{\Phi\left(\frac{m(N_m) + \Delta_m/2 - m(q)}{\sigma_{t-1}}\right) - \Phi\left(\frac{m(1) - \Delta_m/2 - m(q)}{\sigma_{t-1}}\right)}$$

2. Numerical solution:

- $t = T + 1$: for each $i = 1$ to $N_a(t)$ and $j = 1$ to N_m , I evaluate the values of blue-collar and white-collar states: $\hat{V}^b[i, j, t]$ and $\hat{V}^w[i, j, t]$, and determine the value function:
 $\hat{V}[i, j, t] \leftarrow \max \{ \hat{V}^b[i, j, t], \hat{V}^w[i, j, t] \}$.
- $t = 0, \dots, T + 1$: Starting from $t = T$ and solving recursively back to 1, for each $i = 1$ to $N_a(t)$ and $j = 1$ to N_m , I calculate:
 - (a) locate \bar{i} such that $A(\bar{i}, t)$ is the closet grid to $R(A(i, t) + I(t))$

(b) evaluate $\hat{V}^w[i, j, t]$:

$$\hat{V}^w[i, j, t] \leftarrow \max_{1 \leq q \leq i} \left\{ u \left(A(i, t) + I(t) - \frac{A(q, t+1)}{R} \right) + \beta \sum_{k=1}^{N_m} \hat{V}[q, k, t+1] f(k, j, t+1) \right\}$$

(c) evaluate $\hat{V}^b[i, j, t]$ by calling its analytic expression

(d) $V[i, j, t] \leftarrow \max_{k^*(i, j, t)} \{ \hat{V}^b[i, j, t], \hat{V}^w[i, j, t] \}$ and pick the maximizer

(e) ability threshold: $j^*(i, t) \leftarrow \{j | \text{the first } j \text{ such that } \hat{V}^w[i, j, t] \geq \hat{V}^b[i, j, t]\}$