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Essays on Household Savings, Intergenerational Transfers, and Production Network

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Summary

This thesis investigates several topics in Macroeconomics, which contains three self-contained papers, each corresponds to one chapter. A common thread of the three papers is to address macroeconomic questions from the perspective of micro-level theory and data. The first and second chapter explore China's saving rates using household-level theory and surveys. It explains the "camel-shaped" age-saving profile of Chinese households, with a focus on intergenerational transfers. The third chapter explores the propagation of firm-level volatilities in production network. The thesis consists of three chapters, each of which is self-contained and can be read separately.

The first chapter investigates how can intergenerational transfers explain the camel-shaped age-saving profile of Chinese households. Commencing in 2005, a "camel-shaped" age-saving profile of Chinese households began to emerge, which has been documented by various studies. This "camel-shape" feature is puzzling considering that it is at odds with the Life-Cycle Hypothesis. In this paper, we show that the camel-shaped age-saving profile of Chinese households is largely due to the middle-aged households generating a vast amount of intergenerational transfers. These households transfer a significant fraction of their wealth to their children and parents, primarily to their children. In a quantitative overlapping generations (OLG) model, saving rates are linked with altruism of parents and credit constraints of their children, through intergenerational transfers. Saving rates of middle-aged parents decline with altruism ("altruism" channel") and the tightness of their children's credit constraints on housing purchase ("credit constraint" channel). The estimations of life-cycle saving rates based on this model line up well with the data.

The second chapter validates the hypothesis on altruism, credit constraints and saving rates. Using a sample of matched parent-child pairs from the China Family Panel Studies, this chapter tests the "altruism" channel by exploiting the exogenous deaths of children as a natural experiment. Next, I test the "credit constraint" channel from two mechanisms: random allocation of military graduates to different cities, and cross-city variation of mortgage accessibility. Parents whose children are sent by the military to cities with higher housing prices have lower saving rates, ceteris paribus. Access to discounts of down payments for home-buyers leads to an increase in their parents' saving rates.

The third chapter examines whether firm-level idiosyncratic shocks propagate in production networks. This paper identifies idiosyncratic shocks with mergers and acquisitions (M&A).It find that M&A events impose substantial productivities and revenues gains on the target firms. These gains translate into significant output increase and spill over to their customers through input-output linkages. Surprisingly, the indirect effects of M&A on customer firms are much larger than the direct effects on target firms. This comes from the fact that M&As leads to increase of asymmetry in network structure, therefore further amplifies the firm-level shocks.

Résumé

Cette thèse étudie plusieurs sujets dans Macroeconomics, qui contient trois articles indépendants, chacun correspondant à un chapitre. Un fil conducteur des trois articles est d'aborder les questions macroéconomiques du point de vue de la théorie et des données au niveau micro. Le premier et le deuxième chapitre explorent les taux d'épargne de la Chine en utilisant la théorie et les enquêtes au niveau des ménages. Il explique le profil «en forme de dromadaire» des ménages chinois, en mettant l'accent sur les transferts intergénérationnels. Le troisième chapitre explore la propagation des volatilités au niveau de l'entreprise dans le réseau de production. La thèse comprend trois chapitres, chacun étant autonome et pouvant être lu séparément.

Le premier chapitre étudie comment les transferts intergénérationnels peuvent expliquer le profil d'épargne en forme de chameau des ménages chinois. À partir de 2005, un profil «démodé» en forme de chameau des ménages chinois a commencé à émerger, ce qui a été documenté par diverses études. Cette fonctionnalité en «forme de chameau» est déroutante étant donné qu'elle est en contradiction avec l'hypothèse du cycle de vie. Dans un modèle à générations imbriquées quantitatives (OLG), les taux d'épargne sont liés à l'altruisme des parents et aux contraintes de crédit de leurs enfants, au moyen de transferts intergénérationnels. Les taux d'épargne des parents d'âge moyen diminuent avec l'altruisme («altruisme») et l'étroitesse des contraintes de crédit de leurs enfants sur l'achat d'un logement («contrainte de crédit»). Les estimations des taux d'épargne sur le cycle de vie basées sur ce modèle s'alignent bien avec les données.

Le deuxième chapitre valide l'hypothèse sur l'altruisme, les contraintes de crédit et les taux d'épargne. En utilisant un échantillon de couples parent-enfant appariés tirés des études de panel sur la famille en Chine, ce chapitre teste le canal «altruisme» en exploitant la mort exogène des enfants comme une expérience naturelle. Ensuite, je teste le canal «contrainte de crédit» à partir de deux mécanismes: l'allocation aléatoire des diplômés militaires à différentes villes, et la variation inter-villes de l'accessibilité hypothécaire. Les parents dont les enfants sont envoyés par l'armée dans des villes où les prix des logements sont plus élevés ont des taux d'épargne inférieurs, ceteris paribus. L'accès à des escomptes d'acompte pour les acheteurs de maison entraîne une augmentation des taux d'épargne de leurs parents.

Le troisième chapitre examine si les chocs idiosyncratiques au niveau de l'entreprise se propagent dans les réseaux de production. Ce document identifie les chocs idiosyncratiques avec des fusions et acquisitions (M & A). Il constate que les événements de fusions et acquisitions imposent des gains de productivité et de revenus substantiels sur les entreprises cibles. Ces gains se traduisent par une augmentation significative de la production et se répercutent sur leurs clients grâce à des liens intrants-extrants. Étonnamment, les effets indirects des fusions et acquisitions sur les entreprises clientes sont beaucoup plus importants que les effets directs sur les entreprises cibles. Cela vient du fait que les fusions et acquisitions entraînent une augmentation de l'asymétrie dans la structure du réseau, ce qui amplifie encore les chocs au niveau de l'entreprise.

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Chapter 1

Alruism, Intergenerational Transfer and Household Saving

Abstract

This paper investigates the role of intergenerational transfers in explaining the saving behavior of households. In a quantitative overlapping generations (OLG) model, saving rates are linked with the altruism of parents and the credit constraints of their children through intergenerational transfers. The saving rates of middle-aged parents decline with altruism (*the "altruism channel"*) and the tightness of their children's credit constraints on housing purchase (*"credit constraint channel"*). The estimations of life-cycle saving rates based on this model line up well with the data.

Keywords: saving rate, intergenerational transfers, altruism, credit constraint

1.1 Introduction

It is widely acknowledged that the saving rates of Chinese households have been consistently higher than most countries, over the last twenty years. Average Chinese household saving rates have exceeded 30% in the recent decade, compared to less than 10% in the United States and the European Union countries. Commencing in 2005, a *"camel-shaped"* age-saving profile of Chinese households began to emerge, which has been documented by various studies (see Chamon et al. (2013), Choukhmane et al. (2016), Rosenzweig and Zhang (2015)).[1] In addition to the traditional hump-shaped age-saving profile, the "camel-shape" contains an extra trough in the middle, corresponding to households with ages around 55.[2]

This "camel-shape" feature is puzzling considering that it is at odds with the Life-Cycle Hypothesis (see Modigliani (1986)). Life-Cycle Hypothesis expects households to accumulate assets during youth and middle-age to provide for old-age consumption after retirement. Therefore, saving rates should be high during middle-age and negative during senescence. If a households is tracked through his life-time, the age-saving profile should be hump-shaped. Indeed, this hump-shaped age-saving profile has been observed in developed countries, such as US, UK and other OECD countries.

In this paper, we show that the camel-shaped age-saving profile of Chinese households is largely due to the middle-aged households generating a vast amount of intergenerational transfers. These households transfer a significant fraction of their wealth to their children and parents, primarily to their children. Hence, they have lower saving rates than Life-Cycle Hypothesis predicts. These transfers are driven by the desire of parents to support their children to purchase a house. In China, most of the young households buy new a house when they leave their families of origins and start their own families. This generally occurs at the age of around 25 and 55, for children and parents, respectively.

In this paper, two factors are of primary importance in order to understand the large amount of transfer, hence the camel-shaped age-saving profile, that is, *the altruism channel* and the *credit constraints channel*. These two factors are necessary for intergenerational transfers to take place. Stronger altruism lowers saving rates of parents, because more altruistic parents generate larger amount of transfers. In our paper, we refer to this as *"the altruism channel"*. In addition, tighter

[1] Their papers use the Urban Households Survey (UHS). Tthey refer to it as "camel-shaped" age-saving profile.
[2] The age of the household refers to the age of household head.

borrowing constraints on young households also leads to lower saving rates of their parents. In our paper, we refer to this as *the credit constraint channel*. We provide direct empirical evidence that these two channels are of key importance to be able to understand the camel-shaped age-saving profile of the Chinese households.

In this paper we build up a six-period overlapping generation (OLG) model which links saving rates with intergenerational transfers, altruism and credit constraints. In this model, households are assumed to be altruistic, and young households are subject to credit constraints. Transfers and saving rates are endogenously decided in the model. With this model, we first calibrate and estimate the model parameters, and then estimate the life-cycle saving rates accordingly. This forms the basis of our later counterfactual exercises which mimic the reduced form analyses. The comparison of simulated regressions and reduced-form regressions allow us to quantitatively gauge how the model matches the reduced form evidence.

Firstly, our paper is closely related to the literature studying the importance of intergenerational transfers in understanding saving or wealth accumulation of households. Kotlikoff and Summers (1981) and Kotlikoff (1988) use historical U.S. data to estimate the contribution of intergenerational transfers to aggregate capital accumulation. Their estimation implies that more than half of the wealth accumulation stem from transfers across generations. Modigliani (1988) also estimates the proportion of intergenerational transfers in accumulated wealth using three methods: survey method, flow of bequests approach, and estimates using life-cycle models. The paper finds that transfers take up at least one forth of the accumulated savings. And both papers point out that life-cycle models of savings should embrace determinants of intergenerational transfers. Becker (1974) points out that altruism could be modeled as the utility of children directly entering utility of parents. Altonji et al. (1992) focuses on intergenerational altruism as a transfer motive and find that extended-family resources could influence households consumption if it predicts a household's own permanent income. Most of the aforementioned literature focus mainly on bequests when they discuss intergenerational transfers while ignore *inter vivos* transfers, which is the main focus of this paper. Altig and Davis (1989) points out that *inter vivos* transfers are used by households as alternative consumption-smoothing devices, and the altruism needed to motivate large transfers is reasonably small. Gale and Scholz (1994) finds that *inter vivos* transfers are about half as large as transfers that occur upon the death of the donor using Survey of Consumer Finances.

Many empirical papers have examined the motivations of bequests and inter vivos transfers.

Hurd (1987) compared the wealth change of old households with children with that of households without children and concluded that bequests are mostly accidental. Altonji et al. (1997) showed that inter vivos transfers and bequests, respectively, are decreasing in the recipient's income and implied that intergenerational transfers are at least partially motivated by altruism. Nishiyama (2002) develop a model which assumes altruism. In the model, parents and children behave strategically to determine their consumption, saving and transfers. De Nardi (2004) constructs an overlapping-generations model in which parents and children are linked by accidental and voluntary bequests. It shows that the introduction of a bequest motive generates lifetime savings profiles more consistent with the data. Rapoport and Vidal (2007) constructs a neoclassical growth model where intergenerational altruism is endogenous and entails costly sacrifices on the part of parents to acquire such trait. While the acquisition of altruistic traits depends on the economic conditions, altruism determines the level of intergenerational bequests and ultimately the accumulation of physical capital and economic growth. Doepke and Zilibotti (2016) develops a theory of parent-child relations that rationalizes the choice between alternative parenting styles. Parents can affect their children's choices via two channels: either by influencing children's preferences or by imposing direct restrictions on their choice sets. Different parenting styles (authoritarian, authoritative, and permissive) emerge as equilibrium outcomes and are affected both by parental preferences and by the socioeconomic environment. Parenting style, in turn, feeds back into the children's welfare and economic success. The theory is consistent with the decline of authoritarian parenting observed in industrialized countries and with the greater prevalence of more permissive parenting in countries characterized by low inequality.

There is numerous of literature which studies the high saving rate puzzle in China. The explanations mainly fall into four categories: precautionary saving, saving for intergenerational transfers, and saving for after-retirement consumption. This paper belongs to the second category, and particularly focuses on intergenerational transfers related with housing purchase. The investigation of untraditional age-saving profile in China startings with Chamon and Prasad (2010). Their work is the first to document an U-shaped age-saving profile, using an urban household survey (UHS) data set in China. However, their focus is on the high average level of Chinese household saving rates. Our paper also relates to the theoretical and empirical work linking borrowing constraints, housing and savings, starting with Bussière et al. (2013). In their paper, young households are subject to strong borrowing constraints whilst simultaneously facing high housing prices. This explains why they save more than the middle-aged groups. In addition to their concerns, we also explore the mechanism of intergenerational transfers between age groups. Young households who are financially constrained receive transfers from their middle-aged parents, and in turn provide support to them when they are old. This transfer behavior, as shown in our paper, is driven by altruism. That is, parents raise their children in order to provide for their old-age support. This captures the family arrangements within a developing country such as China where the notion holds that children's lives are a continuation of their parents' lives.[3] This transfer is of substantial importance, considering that it is extremely large in magnitude; absolutely and comparatively.[4] This paper is also complementary to Choukhmane et al. (2016), which explores the same age-saving profile using the One-Child Policy of China. Although the mechanisms seem to resemble each other, our work is differentiated from theirs in that we focus on different types of transfers. Choukhmane et al. (2016) study the educational transfer and human capital accumulation, while we study the housing transfer.

The rest of the paper is organized as follows. Section 2.2 provides stylized facts about the age-saving profile and intergenerational transfers that motivate our paper. Section 1.3 provides a three-period overlapping generation (OLG) model which links saving rates with intergenerational transfers, altruism and credit constraints. Section 1.4 extends the three-period model to a quantitative six-period model. Based on the quantitative model, we estimate and calibrate model parameters and estimate the age-saving profile. Section **??** concludes.

1.2 Stylized Facts

Based on various aggregate and household level data sources from China and other countries, this section provides the stylized facts which motivate this study.

First, we display the camel-shaped life-cycle saving rates of Chinese households. We provide evidence that this pattern is robust to various sources of data sets, after tackling measurement error issues. Second, we note the importance of intergenerational transfers related to housing, in absolute and relative terms: young and elderly households receive net transfers while middle-aged households give away transfers. Finally, we show that more than 71.3% of households leave their families of origin and start their own families, at around the age of 25–35. After that, most g on to buy houses for their new families. These findings provide the motivation for this model and the

[3] See Choukhmane et al. (2016)

[4] The elaborate statistical evidence is provided in Section 2.2.

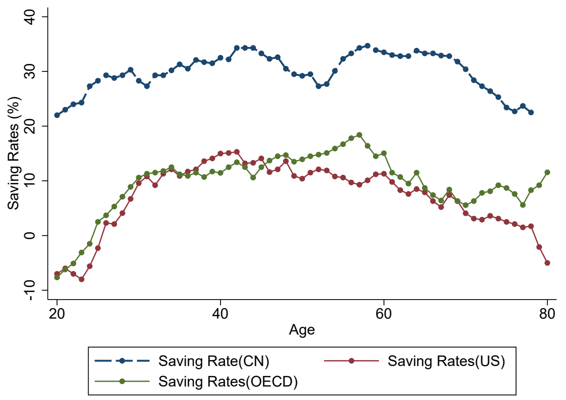


Figure 1.1: Age-saving profiles

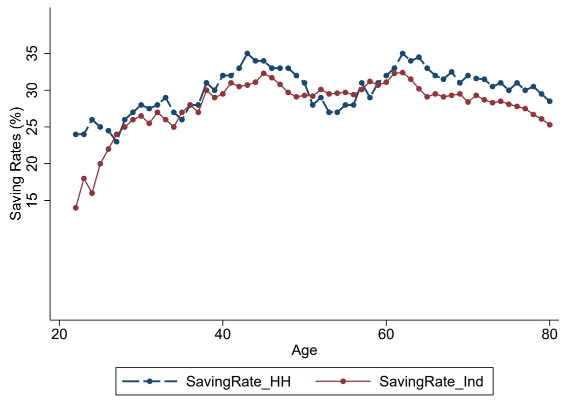


Figure 1.2: Measurement Error

Notes: In Figure 2, "SavingRate_HH" represents the traditional method which uses household head age; while "SavingRate_Ind" addresses the measurement error issues.
Data source:
Figure 1 :CN: National Bureau of Statistics of China (2014); US:Bureau of Labor Statistics;
OECD: https://data.oecd.org/.
Figure 2: CFPS (2008-2014).

reduced form analyses in the following sections.

1.2.1 Age-saving Profile

In this section, we characterize the camel-shaped saving curve of Chinese households, and compare it with the saving curves of other countries. Additionally, we carefully address measurement error issues. We also show that life-cycle saving rate should be distinguished from the cross-section saving curve. Together, these pieces of evidence lead to one conclusion: Chinese households have a robust camel-shaped pattern of life-cycle saving rates.

Figure 1.1 displays saving curves across countries. With regard to China, we use data from the National Statistics Bureau of China (NSBOC) for which there exists a dip of around 12% for the middle-aged households. This dip is observed in each year of the CFPS data, and becomes more pronounced.[5] This camel-shaped pattern is contradictory to the implication of the life-cycle hypothesis which implies that households form a hump-shaped saving curve in their lifetime, see Modigliani (1986). It is also at odds with the saving curves of developed countries such as the U.S. and other OECD countries (see Figure 1.1), which form the traditional hump-shape. Chinese households generate a saving curve with a dip for the middle-aged households in their 80's. Why do Chinese households have different saving behaviors from households in other countries?

[5]The age-saving profiles in year 2008 and 2014 are displayed in Figure 30.

Before answering this question, we show the robustness of this camel-shaped pattern. In the literature review above, we elaborate that this pattern has been documented by many studies, such as Chamon and Prasad (2010), Bussière et al. (2013) and Choukhmane et al. (2016), using different sources of household-level data sets. In our paper, this pattern is found in the China Household Finance Survey (CHFS) data set (see Figure 1.10), the China Family Panel Studies (CFPS) data set (see Figure 1.2), and in data released by the National Statistics Bureau of China (see Figure 1.1).

We next tackle the measurement error issue of saving rates which stems from the difficulty of measuring individual-level savings. Surveys on consumption and savings are mostly based on households as a unit, since people usually consume or save as a family. However, the age of a household is hard to define. In studies on savings, the age of a household head is usually used as proxy which may lead to an upward selection bias for young and elderly households, as young and old individuals are usually less likely to become household heads. Those who are selected as household heads mostly live independently from their parents or children, and tend to earn a higher income than those who co-reside with their families. In addition, individuals with a higher income tend to have higher saving rates. This may lead to an over-estimation of the saving rates of the young and the elderly households, and to a downward bias for middle-aged households. Middle-aged individuals usually live with their young children or elderly parents. Young and old individuals have lower saving rates than middle-aged individuals. Thus, when we count the saving rates of family members as a unit, the saving rates for the middle-aged group is lowered.

Coeurdacier et al. (2015) proposes a method to estimate consumption and savings on an individual level. In this paper, we follow their method in order to tackle the measurement error issue. The idea is to estimate individual-level consumption from household consumption and the composition of families. Details about measurement error control can be found in Appendix .2. Figure 1.2 displays the savings curve after dealing with the measurement error issue. As expected, young and elderly households have an upward bias and middle-aged households have a downward bias. The most important point, however, is that the dip in middle-aged households' saving rates is still salient.

In all of these analyses, we focus on the cross-section of saving curves. However, it is important to note that this is not equivalent to the life-cycle saving rates. In Modigliani (1986), life-cycle savings refer to the saving rates of an individual throughout his lifetime. However, the cross-section savings curve captures the saving rates of individuals of different ages in a given year. Hence, this savings curve may also include time effect and cohort effect. So the *life-cycle saving rates*, or *age-saving profile* (which are used interchangeably in this paper), should be distinguished from the cross-sectional savings curve. There are two ways to estimate the life-cycle saving rates from the cross-sectional data. The first is to estimate the life-cycle saving rates from an OLG model, which is done in Section 1.4 of my paper, using model moments and estimated parameters. Figure 1.10 displays the life-cycle saving rates of Chinese households, which clearly demonstrates that the estimation retains the camel-shape. The second method is to use a decomposition method provided by Chamon and Prasad (2010) and Deaton and Paxson (2000). Using the China Family Panel Study (CFPS), we decompose the time effect and cohort effect from the individual saving rates. The results are robust to controlling time and cohort effects, see Appendix **??** for details.

1.2.2 Intergenerational Transfers and Buying Houses

In this subsection, we describe the importance of intergenerational transfers based on the household-level data sets: CHFS and CFPS. We find that intergenerational transfers for housing are important in both absolute and relative terms. Transfers related to housing have increased dramatically since 2007, compared to other motives, such as education and old-age support. The transfers on housing display age-related patterns, whereby young and elderly households receive transfers, while middle-aged households provide transfers. Finally, we find that most young households purchase houses after they leave their families of origin and start their own family.

The Importance of Intergenerational Transfers Intergenerational transfers are prevalent amongst generations of Chinese people. Making transfers to the young and the elderly is one of the social norms in Chinese culture. In both data sets, more than 80% of middle-aged households claim to have transferred wealth to their children or parents, see Table 1.1. More than 65% of young households respond as having received a transfer from their parents, and more than 60% of elderly households have received transfers from the younger generations (children or grandchildren).

What is more, transfers related to housing make up a large proportion of the total transfers. Figure 1.3 displays the proportions of intergenerational transfers resulting from various types of motives. The most important three motives for transfers are: housing, education and old-age support. The housing and education motives together make up more than 60% of the total transfers. Housing transfers make up more than 30%, which is equivalent to more than 0.3 million RMB, and

Table 1.1: Transfers Among Generations

Households	Incidences of Transfers		Magnitude of Transfers (in million RMB)	
	CHFS (2013)	CFPS (2012)	CHFS (2013)	CFPS (2012)
Young	65.5%	67.4%	0.21	0.29
Middle-aged	82.7%	81.3%	0.25	0.21
Old	67.5%	61.2%	0.08	0.07
Observations	8,438	44,339	8,438	44,339

Notes: in the first two columns, percentages represents the proportion of households who received or generated transfers in their age group. Transfer is defined as the sum of financial and non-financial transfers in yuan. Data Source: CHFS (2013), CFPS (2012)

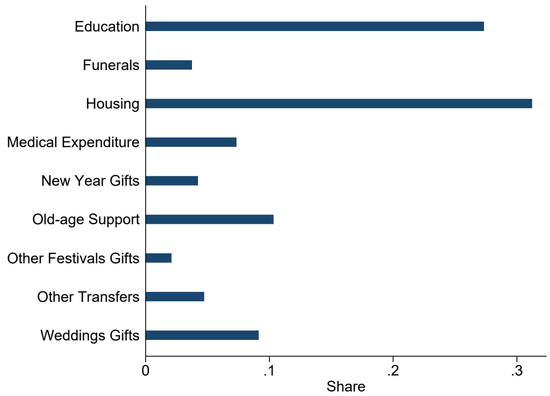


Figure 1.3: Different Categories of Transfers, 2013

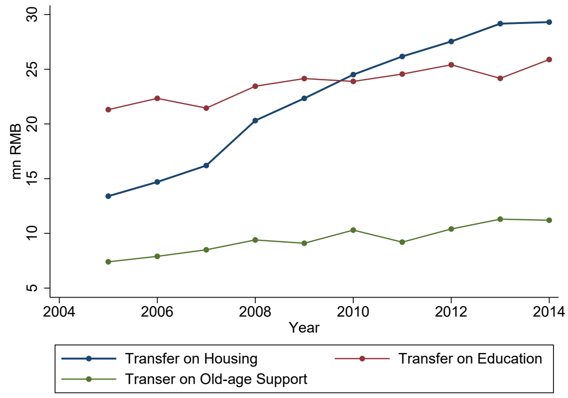


Figure 1.4: Transfers on Education, Housing and Old-age Support

Notes: Data source: CFPS (2013) and Chinese Statistics Year Book (2005-2014). Each category of transfer is defined as the sum of financial and non-financial transfers which fits in that motivation.

this proportion drastically increases from 2007, compared to the other two motives. In Figure 1.4, we observe that transfers in terms of education and old-age support motives climb steadily from 2005, while transfers related to housing experience a large increase in 2007-2010. Notably, this is around the period when China witnessed a large increase in prices on the real estate market.

The Age-Related Pattern of Intergenerational Transfers on Housing Next, we prove that intergenerational transfers on housing are not only important in terms of magnitude and percentage, but also in age-related patterns. Figure 1.7 displays the magnitude and direction of intergenerational transfers on housing for different ages. Positive transfers indicate that the households receive a net transfer, and negative transfers indicate that households give transfers away. In the figure, it is obvious that young and elderly households receive transfers while middle-aged households provide transfers. Generations that provide transfers to others have lower saving rates, while those that

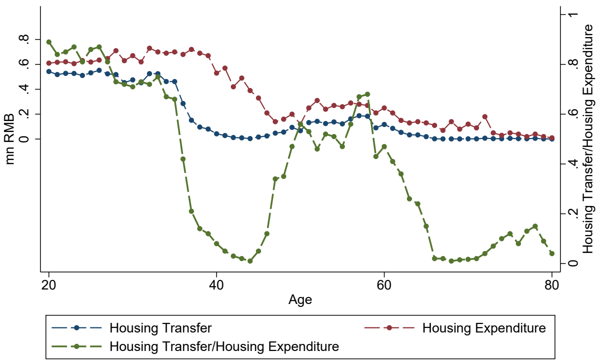


Figure 1.5: Housing Transfers and Housing Expenditure, 2013

Figure 1.6: Housing Transfers and Total Transfers, 2013

Notes: Data source: CHFS (2013). All the transfers and expenditures are displayed in absolute value to obtain positive ratios.The ratio in both figures are high, which implies housing transfers are important in relative to housing expenditures and total transfers.

receive net transfers have higher saving rates. This motivates us to explore the relationship between intergenerational transfers and the age-saving profile.

The Timing of Purchasing Houses In the above paragraphs, we have found potential relationships between intergenerational transfers on housing and the camel-shaped age-saving profile. We now look at the data in regard to when households purchase a house. Figure 1.8 shows the distribution of households who start families and who buy houses against their age. Each point on the curve (or the height of each bar) represents the mass of households who buy houses (or start new families) corresponding to age on the horizontal axis. We find that there are two age peaks for buying houses. One is around age 30-40, and the other is around age 58-63. Together, these two peaks capture more than 70% of housing purchases. In regard to starting families, more than 50% of households start families around age 25-35, and this peak almost overlaps with the first peak of buying a house. This implies that young households leave their families of origin and start their own families around the age 25-35, after which time a large number buy houses for their own families to live in. This finding motivates the important setup shown in the theoretical sections of this paper.

To summarize, in this subsection, we show that the camel-shaped life-cycle pattern of saving rates (or age-saving profile) is robust. We find that intergenerational transfers on housing are important, and contribute to gain importance after year 2008. Moreover, young and elderly households receive transfers while middle-aged households provide transfers. Finally, we show that the timing of buying a house coincides with that of starting a family.

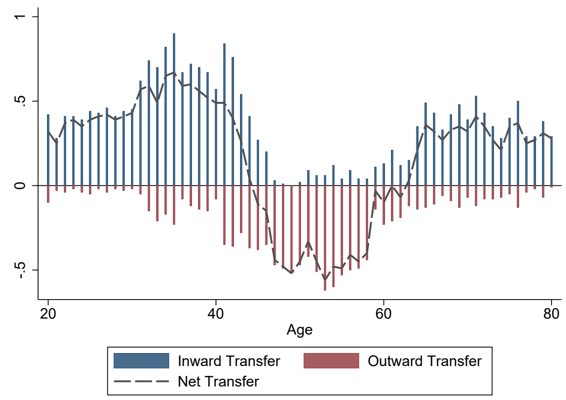


Figure 1.7: Age pattern of intergenerational transfers, 2013

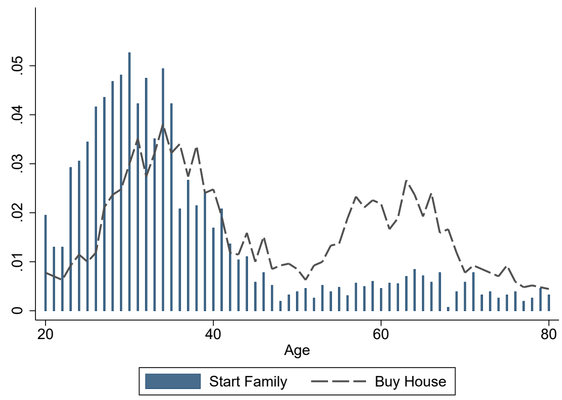


Figure 1.8: Age Density of Starting Families and House Purchasing, 2008-2014

Notes: Data source: CHFS (2013) and CFPS (2010-2014). In the left panel, inward transfer is defined as the transfer that the household receives, *vice versa*. Net transfer is inward transfers less outward transfer. In the right panel, the age of starting family is defined as age of the household head when he/she starts new family. The age of house purchasing is the age when the household purchase the first house.

1.3 A Three-Period OLG Model

In this section, we develop a three-period overlapping generation (OLG) model with housing and intergenerational transfers. Some of het setup is motivated by the empirical findings in the previous section. Here, the focus is only on *inter vivos* transfers. This parsimonious model yields a closed form solution that highlights two channels: the altruism channel and the credit constraint channel.[6] These two channels are important in order to understand the dip in the middle-aged households' saving rates. We present direct reduced form evidence in support of these two channels in Sections 2.3 and 2.4.

Model Setup. Cohort $\{y, t\}$ lives for three periods: youth (y) in period t, middle-age (m) in period $t+1$, and old (o) in period $t+2$. Because of altruistic motives, the agent's *total utility* $V_{y,t}$ is the sum up of his *own utility* $U_{y,t}$ and utilities of his children and parents, denoted by $U_{y,t+1}$ and $U_{y,t-1}$, respectively:

$$V_{y,t} = U_{y,t} + \lambda U_{y,t+1} + \mu U_{y,t-1}. \tag{1.1}$$

Altruism is measured by $(\lambda > 0)$ for the children, and $(\mu > 0)$ for the parents. The agent's own utility $U_{y,t}$ is the discounted sum of his *period utility* $u_{y,t}$:

$$U_{y,t} = u_{y,t} + \beta u_{m,t+1} + \beta^2 u_{o,t+2}. \tag{1.2}$$

[6] This will be discussed in more detail in Proposition 1.

In each period, the agent receives utility from his own consumption and housing:

$$u_{z,\tau} = log(c_{z,\tau}) + \kappa log(H_{z,\tau}), \tag{1.3}$$

where $z = y, m, o$. The period utility $u(z, \tau)$ is separable between consumption $c_{z,\tau}$ and housing $H_{z,\tau}$, with weight κ on housing. Since we assume log-form utilities, consumption in each period is proportional to life-time wealth. We assume that the agent lives in the same house throughout his/her lifetime.

Young agents buy houses $H_{y,t}$ when they leave their families of origin and start their own families. At the same time, they receive transfers $T_{y,t}$ from their altruistic parents. When households grow to middle-aged, they make transfers $T_{y,t+1}$ to their children and $T_{o,t+1}$ to their parents. When they grow old, they do not have a labor income, thus, they receive transfers $T_{o,t+2}$ from their children and use up their savings. These are summarized below:

$$c_{y,t} + a_{y,t} + P_t H_{y,t} \leq w_{y,t} + T_{y,t}, \tag{1.4}$$

$$c_{m,t+1} + a_{m,t+1} + (T_{y,t+1} + T_{o,t+1}) \leq w_{m,t+1} + Ra_{y,t}, \tag{1.5}$$

$$c_{o,t+2} \leq Ra_{m,t+1} + T_{o,t+2}. \tag{1.6}$$

We assume that the housing price in period t, denoted by P_t, and the interest rate R are exogenous. By assuming this, we sever the links of our model with capital and the real estate markets. Next, we present the credit constraint condition:

Assumption 1. Young households are subject to the following credit constraint:

$$-a_{y,t} \leq (1 - \rho) P_t H_{y,t}. \tag{1.7}$$

.

This implies that the young can borrow up to a fraction $1 - \rho$ of the housing value of their mortgage loans, and ρ measures the tightness of the borrowing constraint. This assumption is necessary for obtaining a realistic saving behavior pattern of the young. At optimality, the constraint is binding, so that borrowing increases to the fraction $1 - \rho$ of housing value.

Definition 1. Saving rates is defined as the change of asset levels over disposable income:

$$s_{z,\tau} = \frac{A_{z,\tau} - A_{z,\tau-1}}{w_{z,\tau} \pm T_{z,\tau}}. \tag{1.8}$$

Following this definition, the saving rates of the three cohorts can be derived. Here we display only the saving rates of the middle-aged cohort, as our we focus is on understanding their saving rates trough. Saving rates for the other two cohorts can be seen in Appendix .3.1. Thus:

$$\begin{aligned} s_{m,t+1} =& \frac{\beta}{1+\beta} - \frac{R\beta}{R(1+\beta)} \cdot (T_{o,t+1} + T_{y,t+1} + T_{o,t+2}) \\ &+ \frac{\rho\kappa(1+\beta+\beta^2)(1-R\beta+\beta)}{(1-\rho)(1+\beta)[1+\kappa(1+\beta+\beta^2)]} \cdot (w_{y,t} + T_{y,t}). \end{aligned} \tag{1.9}$$

Next we carefully discuss the determining factors of the middle-aged saving rates $s_{m,t+1}$, and the intuitions behind them. We summarize these factors in Proposition 1 by the altruism mechanism and the credit constraint mechanism.

Proposition 1. *Saving rates of the middle-aged decrease with altruism, the tightness of borrowing constraints, and housing prices of their children:*

$$\frac{\partial s_{m,t+1}}{\partial \lambda} < 0, \frac{\partial s_{m,t+1}}{\partial \mu} < 0$$

$$\frac{\partial s_{m,t+1}}{\partial \rho} < 0, \frac{\partial s_{m,t+1}}{\partial P'_t} < 0$$

$$\frac{\partial s_{m,t+1}}{\partial \lambda}\Big|_{\rho=+\infty} = 0, \quad \frac{\partial s_{m,t+1}}{\partial \rho}\Big|_{\lambda,\ \mu=+\infty} = 0.$$

The proof is included in Appendix .3.1.

This proposition lays out the two channels mentioned previously: the altruism channel and the credit constraint channel. Regarding the altruism channel, the saving rates of middle-aged households decline with altruism. This is intuitive. If the altruism motive is stronger, parents generate a larger number of transfers. Larger transfers depress saving rates because fewer resources are available for savings.[7] The second line denotes the credit constraint channel: the saving rates of the middle-aged households decrease with the tightness of credit constraints ρ. This is also intuitive. As it is more difficult to raise money from the financial market, young households receive a larger

[7]There is another effect which points to the opposite direction. Transfers decrease life time wealth to which consumption is proportional. This slightly push up savings. When combined, the first effect dominates the second one. Therefore, the total effect of altruism on saving rates of the middle-aged parents is negative.

transfer from their parents.[8] The third line identifies that both altruism and a credit constraint are necessary to generate the implications above.

1.4 Estimation of Age-saving Profile

In this section, we extend the baseline three-period model into a six-period model. Agents now live for six periods, with two periods in youth, middle-age and old-age, respectively. Transfers take place in all periods.[9]

There are two differences in this setup from the three-period model. First, we assume that young households make house purchasing decisions in the second period of their youth only. This assumption is motivated by the observation of house purchasing behavior in the CFPS data set, displayed in Figure **??**. Section 2.2 shows that one peak of buying houses corresponds to the age of 30-40, and that this peak captures more than 70% of house purchasing by young households. Second, we assume that young households are subject to borrowing constraints in the second period of youth only, without loss of generality. In the first period, households generate positive savings with or without borrowing constraints, because they optimally choose to save for house purchasing in the next period.

The intuition of the altruism channel and credit constraint channel remain unchanged. They are summarized in Proposition 2 in Appendix .3.3. With this model, we first calibrate and estimate the model parameters, and then accordingly estimate the life-cycle saving rates. This forms the basis of our later counterfactual exercises which mimic the reduced form analyses in Sections 2.3 and 2.4. The counterfactual experiment allows us to quantitatively gauge how the model matches the reduced form evidence.

1.4.1 Estimation of Parameters

There are seven parameters: discount factor β, altruism parameters λ (to children) and μ (to parents), utility weight on housing κ, interest rate R, credit constraint ρ, and income growth λ. These seven parameters can be divided into two groups in terms of estimation strategy. Group 1 consists of parameters β, R, λ and ρ. They can be estimated independently of the model or provided by

[8] There is also a minor opposite effect. As explained above in Equation 14, tighter credit constraint discourages young households to buy expensive houses. This leads the transfers to drop. While the combined effect is negative.

[9] Details of model setup can be seen in Appendix .3.2.

other studies. Group 2 consists of parameters κ, λ and μ, which estimated targeting on moment conditions.

Table 1.2: *Calibrated Parameters*

Parameter		Value	Target/Data
R	interest rate	1.05	Long-term interest rate, PBC
β	discount rate	0.99	Avg. Saving Rate (CHFS, 2013)
ω	annual gr. of income	6.23%	CHFS data
ρ	credit constraint	0.734	Mortgage loan
κ	utility weight on housing	0.257	Housing expenditure

First, we explain how the parameters in Table 1.2 are calibrated. The data used to estimate the parameters is the China Household Finance Survey (CHFS).[10] *Real return on assets R*. There is a lack of empirical observations on the real return on assets faced by Chinese households. In this paper, we use the long-term interest rate released by People's Bank of China in 2013. *Discount Factor β* is calibrated targeting on the average saving rates of households in CHFS data set.[11] *Income growth rate ω*. The income growth rate is estimated using the income data in CHFS. *Credit constraint ρ*. ρ is estimated using the ratio of mortgage loan and value of house related to it.[12] *Utility weight on housing κ*. The utility weight on housing is calibrated targeting on the total expenditure on housing.

Then I explain in details how I estimate parameters in Table 1.3. These two parameters are estimated using generalized method of moments (GMM).[13] The F.O.Cs displayed in Appendix .3.2 (Equation 21, Equation 26 and Equation 27) yield 3 moment conditions for each household:

$$h(\boldsymbol{\gamma}, \boldsymbol{\zeta}, \boldsymbol{X}) = \boldsymbol{E}(\boldsymbol{M} \cdot \boldsymbol{X_1} - \boldsymbol{X_2}) = \boldsymbol{0}$$

where $\boldsymbol{\gamma}$ stands for the vector of parameters to be estimated: $\boldsymbol{\gamma} = (\kappa\ \lambda\ \mu)$. $\boldsymbol{\zeta}$ represents the parameters which have been estimated above: $\boldsymbol{\zeta} = (\beta\ R\ \lambda\ \rho)$. $\boldsymbol{X}$ denotes the data matrix, which is the combination of $\boldsymbol{X_1} = (c_{y,t+1}\ \ c_{y,t+2}\ \ c_{o,t+2})'$ and $\boldsymbol{X_2} = (P_{t+1}H_{y,t+1}\ \ c_{m,t+2}\ \ c_{m,t+2})'$. And $\boldsymbol{M}$ denotes

[10] Data description is displayed in Appendix .1.2.

[11] The estimation of saving rates are robust to (β, R) pairs. The results of robustness check are displayed in Appendix .5.

[12] The credit constraint in this model will be binding, then I have:

$$\frac{a_{y,t+1}}{P_{t+1}H_{y,t+1}} = \rho$$

So ρ can be obtained by taking the ratio of mortgage loan and the value of house.

[13] A robustness check using OLS regressions generate similar results. Details of the robustness check is displayed in Appendix .5.1.

the diagonal matrix:

$$M = \begin{bmatrix} m & 0 & 0 \\ 0 & \dfrac{1+\beta+m}{\lambda(1+\beta)} & 0 \\ 0 & 0 & \dfrac{R^4}{\mu} \end{bmatrix}$$

where $m = \dfrac{\kappa \sum_{t=1}^{6} \beta^{t-1}}{1-\rho}$. Given the data on households consumption and housing $\boldsymbol{X}$, I would estimate:

$$\hat{\gamma} = \text{argmin}_{\tilde{\gamma}} \quad g(\tilde{\gamma}, \zeta, \boldsymbol{X})' \, \boldsymbol{W_g} \, g(\tilde{\gamma}, \zeta, \boldsymbol{X})$$

where $\boldsymbol{W_g}$ is the weighting matrix and $g(\gamma, \zeta, \boldsymbol{X})$ is the empirical counterpart to $h(\gamma, \zeta, \boldsymbol{X})$:

$$\begin{aligned} g(\gamma, \zeta, \boldsymbol{X}) &= \frac{1}{N}\sum_{i=1}^{N} \quad h(\gamma, \zeta, \boldsymbol{X_i}) \\ &= \begin{bmatrix} m & 0 & 0 \\ 0 & \dfrac{1+\beta+m}{\lambda(1+\beta)} & 0 \\ 0 & 0 & \dfrac{R^4}{\mu} \end{bmatrix} \cdot \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} c_{iy,t+1} \\ c_{iy,t+2} \\ c_{io,t+2} \end{bmatrix} + \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} P_{i,t+1}H_{iy,t+1} \\ c_{im,t+2} \\ c_{im,t+2} \end{bmatrix} \end{aligned} \tag{1.10}$$

Then I use the standard two-step estimator for GMM. In this case, the weighting matrix $\boldsymbol{W_g} = Cov\ [g(\hat{\gamma}_I, \zeta, \boldsymbol{X})]^{-1}$, where $\hat{\gamma}_I$ is the first-step estimator of γ using identity matrix as the initial weighting matrix. The results are displayed in Table 1.3.[14]

Table 1.3: *Estimated Parameters: GMM*

Parameter		Two-Step
λ	altruism on children	0.631***
		(0.042)
μ	altruism on parents	0.277***
		(0.073)

1.4.2 Estimation of Life-Cycle Saving Rates

In this section, I estimate a curve of life-cycle saving rates, using both our model and estimated parameters. The result is displayed in Figure 1.10. To obtain this curve, for each household i, I not only estimate s_{it} in the survey year t, but also her saving rates before and after survey year: $s_{i\tau}$, for

[14]The weighting matrix $\boldsymbol{W_g} = Cov\ [g(\hat{\gamma}_I, \zeta, \boldsymbol{X})]^{-1}$ is not the optimal weighting matrix, however it does not affects consistency of the estimator.

$\forall \tau \neq t$.

To achieve this, I firstly create six bins in terms of households' ages: 20-30, 31-40, 41-50, 51-60, 61-70 and 71-80. Each bin echoes one formula of saving rates in our model, summarized by Equation 46 to Equation 51. Each household fits one bin according to her age in the survey year. For instance, if household i is 42 in the survey year 2013, she goes into the third bin. Then, I estimate not only household i's current saving rate (saving rate in age 42), but also saving rates in other bins (saving rates if she would be age 22, 32, 52, 62 and 72). In other words, I estimate life-cycle saving rates $s_{i,a}$ for household i, where a represents the age. Therefore, for each household i, I generate 6 saving rates $s_{i,a}$ (a=1, 2, 3, 4, 5, 6). Then I take the average of saving rates for the same age: $s(a) = \sum_{i \in a} s_{i,a}$. And this function $s(a)$ will be the life-cycle saving rates pictured in Figure 1.10.

Then I explain how I estimate $s_{i,a}$ for each individual. Let $\Gamma = (\beta, R, \lambda, \lambda, \mu, \kappa, \rho)'$ (or $\Gamma = (\gamma, \zeta)'$ in accordance with Section 1.4.1) represent the vector which summarizes all the parameters of the model. According to Equation 46 – Equation 51, I summarize saving rates for all the ages below.[15]

$$s_{i,a} = F_a(\boldsymbol{w_i}, \boldsymbol{T_i}; \Gamma) \tag{1.11}$$

$\boldsymbol{w_i}$ is a vector of life-cycle labor income. It can be estimated using the current labor income and labor income growth rate λ estimated in Table 1.2. $\boldsymbol{T_i}$ is a vector of life-cycle transfers. And notice that the age only affects the function form F_a which echoes the formulas of saving rates summarized by Equation 46 – Equation 51.

The obstacle to estimate life-cycle saving rates is to estimate life-cycle intergenerational transfers. Here, I introduce briefly the strategy, and all the technical details are summarized in Appendix .4.1. Transfers which take place in the latter periods recursively depend on transfer which take place in the earlier periods:

$$T_{g,t} = F(T_{g,t-1}, T_{g,t-2}), \quad g = y, m, o$$

For instance, the transfers which old parents receive depend on the transfers which they made to their children, and furthermore depend on the transfers they received when they were young. We are able to observe some of the past transfers $T_{g,t-\tau}$ in our data. Taking advantage of these observations and the F.O.C.s of intergenerational transfers gives rise to the estimation of $T_{g,t}$. Figure 1.9 displays the pattern of *life-cycle intergenerational transfers*.

This figure displays the inward transfers. In Figure 1.9, positive transfers mean that households

[15] Technical Details to estimate life-cycle saving rates can be seen in Appendix .5.

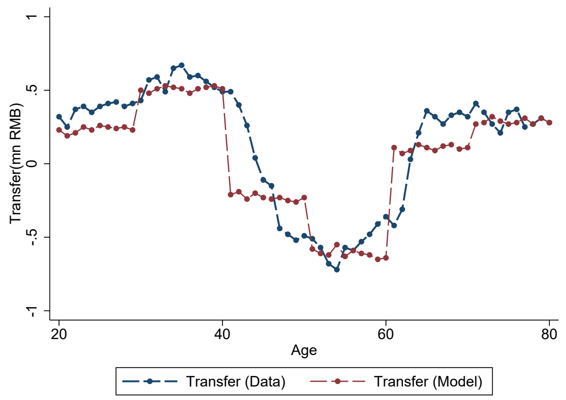


Figure 1.9: Intergenerational Transfer: data and estimation

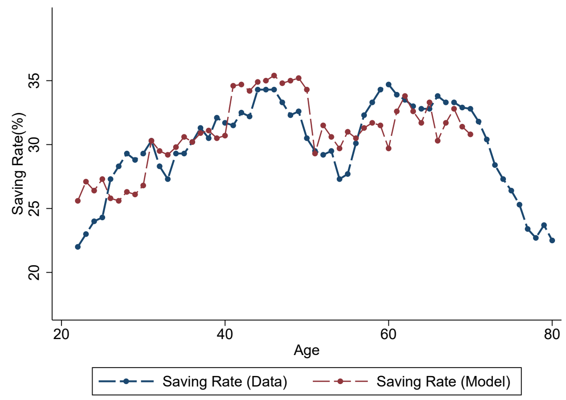


Figure 1.10: Life-Cycle Saving Rates: data and estimation

Data source: China Household Finance Survey

receive net transfers, *vice versa*. The estimated life-cycle transfers form a "camel-shaped" curve. This means young and elderly households receive net transfers while middle-aged households send transfers. This is in accordance with the data observation.

With the estimated parameter vector Γ and the estimated income and transfer pattern $(\boldsymbol{w_i}, \boldsymbol{T_i})$, I are able to estimate life-cycle saving rates for each household. This can be done using Equation 1.11:

$$s_{a,i} = F_a(\boldsymbol{w_i}, \boldsymbol{T_i}; \Gamma)$$

For each given age, I take the average of saving rates: $s(a) = \sum_{i \in a} F_a(\boldsymbol{w_i}, \boldsymbol{T_i}; \Gamma)$. Therefore, I are able to depict the age-saving curve $s(a)$ in Figure 1.10. It is important to point out that this age-saving profile captures the life-cycle pattern of saving rates. In other words, this curve records a "*average*" household's saving rates through her life-time. This "*average*" household does not exist. It is generated by averaging the estimated life-cycle saving rates for each household in our sample. This life-cycle saving rates, or age-saving pattern, should be distinguished from the cross-section saving rates. The cross-section saving rates display the saving rates of different households with different ages. It does not ideally capture the life-cycle characteristic of saving behavior.

In Figure 1.10, the age-saving profile shows up as a continuous function rather than a hybrid function. It might be counter-intuitive at the first glance, since there are only six equations for the saving rates (Equation 46 to Equation 51), or six bins to fit all the households. However, this could be understood by looking into Equation 1.11. Saving rate $s_{(a)}$ will be a piecewise function if and only if households belonging to the same bin have same saving rates, *a.k.a.* :

$$s(a,i) = s(a,j), \quad for \ \forall \ (i,j) \in \{(i,j)|F_{a,i}(\cdot) = F_{a,j}(\cdot)\}$$

However, I know from Equation 1.11 that saving rate of household i with age a depend on her income vector $\boldsymbol{w_i}$ and transfer vector $\boldsymbol{T_i}$. As discussed above, the life-cycle income and transfer are estimated using both F.O.Cs and data observations. Therefore, the variation of intra-bin saving rates results from the historical transfer pattern.

In Figure 1.10, I observe that the average household savings rates is 32.73% in our data observations, and 31.38% for our model estimation. Our estimation is higher than the data observation for households with age of 30–50. And the average gap is around 2.7%. This stems from the estimation of intergenerational transfer in Figure 1.9. Our model generates higher transfers for young households than the data. Higher transfer lead to higher saving rates of young households. [16] Also, I observe a slight over-estimation of elderly households' saving rates. One explanation is that our model does not consider precautionary saving related with uncertainties. In reality, old households tend to save more to insure against the shocks they might face in the future. Exclusion of precautionary saving leads to a gap of 1.73%.

1.4.3 Forecasts of Chinese Aggregate Saving Rates

In this section, I form two out-of-sample forecasts. We estimate saving rates in year 2016[17] and year 2023. Through these forecasts, I would like to explore how demographic pattern would contribute to changes of household savings, or aggregate savings in China.

We keep the same parameters in Table 1.2 and Table 1.3, while allow for changes in demographic pattern. In other words, I estimate $s(a) = \sum_{i \in a} F_a(\boldsymbol{w_i}, \boldsymbol{T_i}; \Gamma)$ with different sets $\{i \in a\}$.

Here, based on our sample in 2013, I estimate the population projection for 2016 and 2023.[18] Figure 32 displays the population projection. The left figure displays the 3 year projection, and the right figure displays the 10 year projection. The demographics do not change a lot. Percentage of old households increases by around 7.8% in 2023, compared to 2013. Up till then, the elderly makes

[16] The intuition is buried in Equation 15, and is discussed in the paragraph following it.

[17] The reason for 3 year is that I could compare the estimation with data released by National Bureau of Statistics of China.

[18] The main obstacle to estimate future demographics is the unobserved death rates faced by different age cohorts. To tackle with this issue, I follow the method discussed in Lee and Carter (1992), in which they estimate mortality rates by age groups.

Table 1.4: Saving Rates Simulation I, 3-yr & 10-yr forecast

	2013		2016		2023
	Model	CHFS Data	Model	NSBoC Data	Model
	(1)	(2)	(1)	(2)	(1)
Aggregate	31.71%	29.10%	28.79%	28.51%	24.91%
young	27.87%	25.10%	25.17%	27.83%	26.21%
middle-aged	35.19%	31.67%	34.25%	35.39%	33.08%
old	26.81%	25.54%	23.01%	22.81%	23.21%

Note: Data source: CHFS and National Statistics Bureau of China (NSBoC).

up around one quarter of the population. This result is consistent with predictions made by other researchers on Chinese demographics.

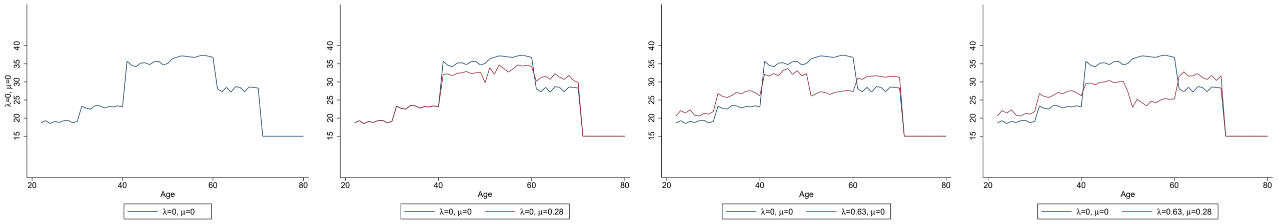
In Table 1.4, I display the estimation of household saving rates for year 2013, 2016 and 2023. The first column displays the model estimation of saving rates for 2013. Right to it is the data observation of CHFS. This is the same as Figure 1.10. The third column displays estimation for year 2016. The fourth column displays the official data released by National Statistic Bureau of China. The last column displays the estimation of year 2023.

Comparing saving rates in three years, I observe that aggregate saving rates decline by 6.8% from year 2013 to 2023. However, saving rates for different age groups do not change a lot. What drives the decline of the aggregate saving rates is the changing demographics. From year 2014 to 2023, the fraction of elderly households increase. The elderly households have lower saving rates than the other two age groups. And this pulls down the aggregate saving rate by 6.8%.

1.4.4 Counterfactual Analyses

Proposition 1 and Proposition 2 yield two implications. Stronger altruistic motivation towards children leads to lower saving rates of the middle-aged parents (the altruism channel). Tighter credit constraint on housing leads to lower saving rates of the middle-aged parents (credit constraint channel). The intuition has been elaborated in Section 1.3. In the next two sections, I directly test for those two channels using CPFS data sets.

First, I display the counterfactual analysis in which I shut down altruism for children and parents, respectively. Therefore, in Figure 1.11a, I set the scenario ($\lambda = 0, \mu = 0$) as the benchmark. Then I compare ($\lambda = 0, \mu = 0.28$), ($\lambda = 0.63, \mu = 0$) and ($\lambda = 0.63, \mu = 0.28$) with the benchmark case in Figure 1.11b, Figure 1.11c and Figure 1.11d below.



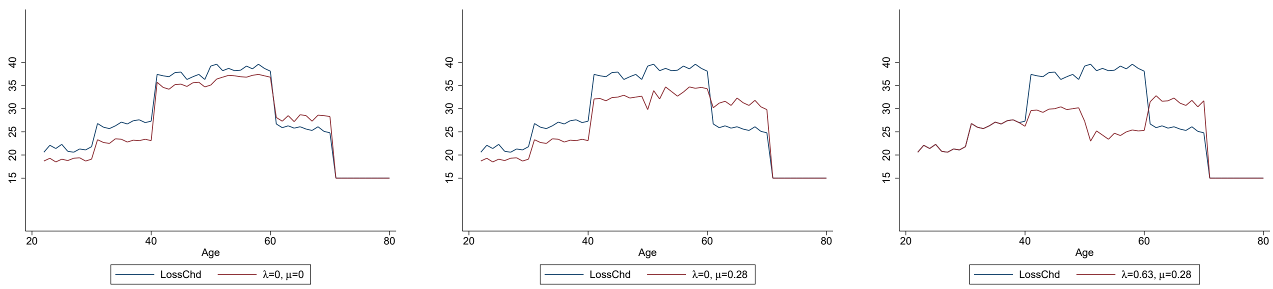
(a) (b) (c) (d)

1.5 Experiments: Accidental Death and Random Allocation of Children

In this section, I launch two experiments in the model: accidental deaths of children and random allocation of children's locations. Both experiments mimic the reduced-form analyses in Section 2.3 and Section 2.4. In this section, I obtain simulation of saving rates under both two scenarios. The idea is to compare the reduced-form estimates using simulated saving rates with estimates using saving rates coming from data. The difference between two estimates gauges quantitatively whether the model is in line with the reality. Herein I introduce the experiments and the simulated saving rates. The reduced-form estimates are displayed in Section 2.3 and 2.4, respectively.

1.5.1 Accidental Death of Children

Then, I launch an experiment in the model. For the middle-aged and old households (40-80), I give them an unpredicted death shock about their children. And this shock, by design, is orthogonal to all other characteristics of the households (income, saving rates, etc). The shock is realized in the first period of being middle-aged (30-40). How to explain the counterfactual estimation. For the middle-aged households, it is the saving rate if they lose their children. For the old households, it is the saving rate if they lost their children when they were middle-aged.

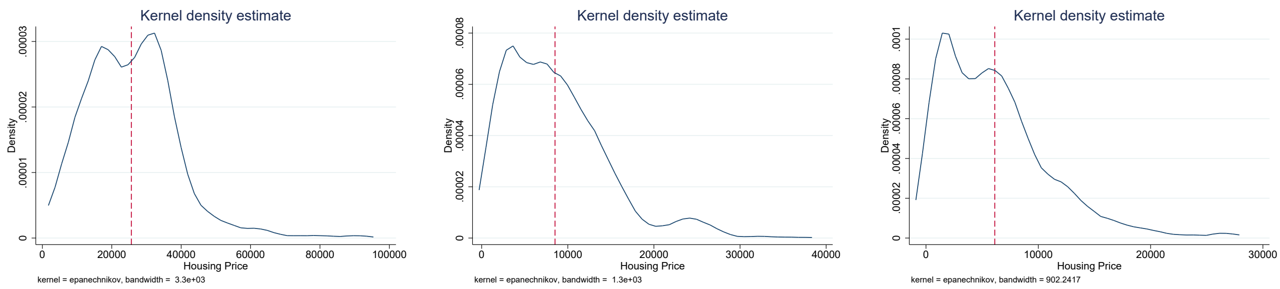


(a) (b) (c)

1.5.2 Random Allocation of Children

In this section, I launch an experiment where children are randomly allocated to cities different from their current location. The idea is to randomly assign every children a housing price. The housing prices follow the distribution backed out from the data set. Then I feed the new housing prices into Equation 1.11, instead of their current housing prices.

Firstly, I back out the joint distribution of housing prices and cities $\mathscr{P}$ from the CHFS data. The reason to use the joint distribution is that the information of cities are needed when formulating the reduced-form regression using simulated saving rates. Figure 1.13a, 1.13b and 1.13c display the conditional distribution of housing prices for children living in high price, medium price, and low price cities: $f(Housingprice|City \in H), f(Housingprice|City \in M), f(Housingprice|City \in L)$. The classification of cities can be seen in footnote 16. Figure 1.14 displays the distribution of parents whose children living in different cities. The distribution of cities $F(City \in H), F(City \in M), F(City \in L)$can also be obtained from the data, therefore we figure out the joint distribution of city and housing prices $\mathscr{P} = f(HousingPrice, City) = f(HousingPrice|City) \cdot F(City)$.



(a) High Price Cities (b) Medium Price Cities (c) Low Price Cities

Notes: Data Source: CHFS (2011). Housing prices is measured by the selling price of residential real estate.

Next, we feed distribution $\mathscr{P}$ into our estimation Equation 1.11 and obtain the simulated saving rates for parents $s_{i,a} = F_a(\boldsymbol{w_i}, \boldsymbol{T_i}, \mathscr{P}; \Gamma)$. Figure 1.15 displays the simulated saving rates of parents whose children live in high prices, medium prices, and low prices cities. Parents whose children living in high prices cities have the lowest saving rates. Because they give the largest amount of transfers to their children. This is consistent with the model implication, and the observation from dataset, see Figure 2.7.

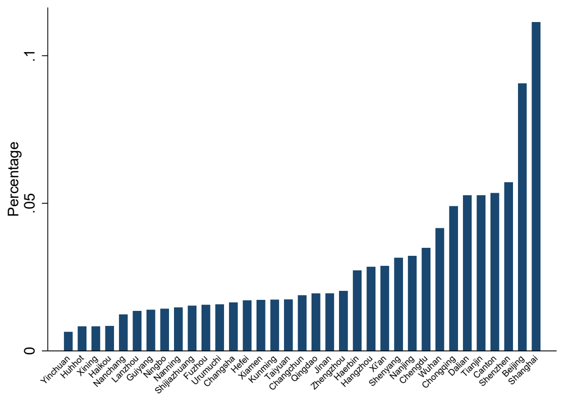


Figure 1.14: Distribution of Location

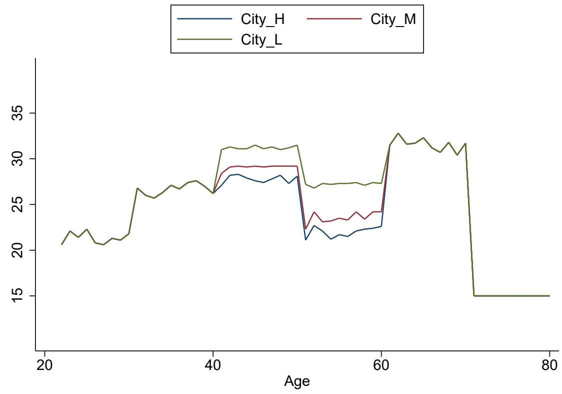


Figure 1.15: Simulation: Random Allocation of Children

Notes: Data Source: CHFS (2011, 2013). Cities refer to the location of children. The simulated saving rates are highest for parents (age 40-60) whose children live in low prices cities, and lowest for parents whose children live in high prices cities. Simulated saving rates of young and old households are the same as in Figure 1.10.

1.6 Conclusion

In this paper, we investigate the role of intergenerational transfers in explaining the "camel-shaped" age-saving profile of Chinese households. In a quantitative overlapping generations (OLG) model, saving rates are linked with the altruism of parents and the credit constraints of their children, through intergenerational transfers. Two channels are important: the altruism channel and the credit constraint channel. The altruism channel implies that the saving rates of middle-aged parents decline with their strength of altruism. The credit constraint channel implies that saving rates of parents decline with the tightness of their children's credit constraints on house purchasing. Next we validate the two channels using the CFPS and CHFS data sets.

Using the China Household Finance Survey data set, we calibrate/estimate model parameters and accordingly estimate the life-cycle saving rates for Chinese households. These saving rates are in line with the saving rates calculated from the data. Moreover, we launch a counterfactual experiment in which parents are shocked by the accidental deaths of their children. This mimics the natural experiment in the reduced form analysis. The counterfactual results imply that altruism towards children is essential in order to generate "camel-shaped" life-cycle saving rates.

Chapter 2

Understanding the Saving Behavior of Chinese Households: Intergenerational Transfers and Housing

Abstract

This paper investigates the role of intergenerational transfers in explaining the saving behavior of households. In this paper, saving rates are linked with the altruism of parents and the credit constraints of their children through intergenerational transfers. The saving rates of middle-aged parents decline with altruism (*the "altruism channel"*) and the tightness of their children's credit constraints on housing purchase (*"credit constraint channel"*). The estimations of life-cycle saving rates based on this model line up well with the data. Using a sample of matched parent-child pairs from household level data in China, we test the altruism channel by exploiting the exogenous deaths of children as a natural experiment. Next, we test the credit constraint channel using two mechanisms: the random allocation of military graduates to different cities; and the cross-city variation of mortgage accessibility. Parents whose children are sent by the military to cities with higher housing prices have lower saving rates, *ceteris paribus*. Access to discounts of down-payments for home buyers leads to an increase in their parents' saving rates.

Keywords: saving rate, intergenerational transfers, altruism, credit constraint

2.1 Introduction

In 2005, a *"camel-shaped"* age-saving profile of Chinese households began to emerge, which has been documented by various studies (see Chamon et al. (2013), Choukhmane et al. (2016), Rosenzweig and Zhang (2015).[1] In addition to the traditional hump-shaped age-saving profile, the "camel-shape" contains an extra trough in the middle, corresponding to households with ages around 55.[2] This "camel-shape" feature is puzzling considering that it is at odds with the Life-Cycle Hypothesis (see Modigliani (1986)). Life-Cycle Hypothesis expects households to accumulate assets during youth and middle-age to provide for old-age consumption after retirement. Therefore, saving rates should be high during middle-age and negative during senescence. If a households is tracked through his life-time, the age-saving profile should be hump-shaped. Indeed, this hump-shaped age-saving profile has been observed in developed countries, such as US, UK and other OECD countries.

In this paper, we show that the camel-shaped age-saving profile of Chinese households is largely due to the middle-aged households generating a vast amount of intergenerational transfers. These households transfer a significant fraction of their wealth to their children and parents, primarily to their children. Hence, they have lower saving rates than Life-Cycle Hypothesis predicts. These transfers are driven by the desire of parents to support their children to purchase a house. In China, most of the young households buy new a house when they leave their families of origins and start their own families. This generally occurs at the age of around 25 and 55, for children and parents, respectively.

In this paper, two factors are of primary importance in order to understand the large amount of transfer, hence the camel-shaped age-saving profile, that is, *the altruism channel* and the *credit constraints channel*. These two factors are necessary for intergenerational transfers to take place. Stronger altruism lowers saving rates of parents, because more altruistic parents generate larger amount of transfers. In our paper, we refer to this as *"the altruism channel"*. In addition, tighter borrowing constraints on young households also leads to lower saving rates of their parents. In our paper, we refer to this as *the credit constraint channel*. We provide direct empirical evidence that these two channels are of key importance to be able to understand the camel-shaped age-saving profile of the Chinese households.

[1] Their papers use the Urban Households Survey (UHS). Tthey refer to it as "camel-shaped" age-saving profile.
[2] The age of the household refers to the age of household head.

We provide direct evidence for the altruism channel and the credit constraint channel. Regarding the altruism channel, we identify the effects of altruism on saving rates by exploiting the exogenous deaths of children as a natural experiment. Around 7% of households have experienced the loss of their children due to accidents, such as traffic accidents, disease, natural disasters etc. They were adult children at the time of their death with their middle-aged parents no longer able to procreate. As a consequence, their altruism towards their children ceased with the loss of their children. We find that non-altruistic parents have an 11% drop in saving rates compared to altruistic parents. What is more, we are able to identify the path of saving rates for parents. The simulated regression yields very close results to the reduced form regression.

Furthermore, we test the credit constraint channel from two mechanisms: access to mortgage loans and housing prices. Using cross-section variations in the implementation of Client Express Loan (CEL) and average housing prices, we compare the saving rates of parents whose children live in different cities. However, children's city choices may be correlated with unobserved family characteristics which also affect parents' saving rates. To tackle this endogeneity issue, we exploit the exogenous allocation of military cadets in China as a randomized controlled trials (RCT) for both mechanisms.

In our data there are around 5.31% (c.a. 873) households that graduate from military academies. After graduation, these military cadets are randomly allocated to different cities by the People's Liberation Army to become military officers or civilians. The decision-making process of job assignments is highly centralized in the P.L.A. General Political Division, and highly demand-driven. This features leads to locations of military cadets exogenous from characteristics of their parents. find that access to Client Express Loan (CEL) leads to a drop of around 8% in parents' saving rates. Also, when comparing children living in high price cities and low price cities, we find a difference around 10% in their parents' saving rates. These two tests together validate the credit constraint that tighter borrowing constraint and higher housing prices lead to lower saving rates for middle-aged parents.

Becker (1974) points out that altruism could be modeled as the utility of children directly entering utility of parents. Altonji et al. (1992) focuses on intergenerational altruism as a transfer motive and find that extended-family resources could influence households consumption if it predicts a household's own permanent income. Most of the aforementioned literature focus mainly on bequests when they discuss intergenerational transfers while ignore *inter vivos* transfers, which is the main focus of this paper. Altig and Davis (1989) points out that *inter vivos* transfers are used by households as alternative consumption-smoothing devices, and the altruism needed to motivate large transfers is reasonably small. Gale and Scholz (1994) finds that *inter vivos* transfers are about half as large as transfers that occur upon the death of the donor using Survey of Consumer Finances.

Many empirical papers have examined the motivations of bequests and inter vivos transfers. Hurd (1987) compared the wealth change of old households with children with that of households without children and concluded that bequests are mostly accidental. Altonji et al. (1997) showed that inter vivos transfers and bequests, respectively, are decreasing in the recipient's income and implied that intergenerational transfers are at least partially motivated by altruism. Nishiyama (2002) develop a model which assumes altruism. In the model, parents and children behave strategically to determine their consumption, saving and transfers. De Nardi (2004) constructs an overlapping-generations model in which parents and children are linked by accidental and voluntary bequests. It shows that the introduction of a bequest motive generates lifetime savings profiles more consistent with the data. Rapoport and Vidal (2007) constructs a neoclassical growth model where intergenerational altruism is endogenous and entails costly sacrifices on the part of parents to acquire such trait. While the acquisition of altruistic traits depends on the economic conditions, altruism determines the level of intergenerational bequests and ultimately the accumulation of physical capital and economic growth. Doepke and Zilibotti (2016) develops a theory of parent-child relations that rationalizes the choice between alternative parenting styles. Parents can affect their children's choices via two channels: either by influencing children's preferences or by imposing direct restrictions on their choice sets. Different parenting styles (authoritarian, authoritative, and permissive) emerge as equilibrium outcomes and are affected both by parental preferences and by the socioeconomic environment. Parenting style, in turn, feeds back into the children's welfare and economic success. The theory is consistent with the decline of authoritarian parenting observed in industrialized countries and with the greater prevalence of more permissive parenting in countries characterized by low inequality.

There is numerous of literature which studies the high saving rate puzzle in China. The explanations mainly fall into four categories: precautionary saving, saving for intergenerational transfers, and saving for after-retirement consumption. This paper belongs to the second category, and particularly focuses on intergenerational transfers related with housing purchase. The investigation of untraditional age-saving profile in China startings with Chamon and Prasad (2010). Their work is the first to document an U-shaped age-saving profile, using an urban household survey (UHS) data set in China. However, their focus is on the high average level of Chinese household saving rates. Our paper also relates to the theoretical and empirical work linking borrowing constraints, housing and savings, starting with Bussière et al. (2013). In their paper, young households are subject to strong borrowing constraints whilst simultaneously facing high housing prices. This explains why they save more than the middle-aged groups. In addition to their concerns, we also explore the mechanism of intergenerational transfers between age groups. Young households who are financially constrained receive transfers from their middle-aged parents, and in turn provide support to them when they are old. This transfer behavior, as shown in our paper, is driven by altruism. That is, parents raise their children in order to provide for their old-age support. This captures the family arrangements within a developing country such as China where the notion holds that children's lives are a continuation of their parents' lives.[3] This transfer is of substantial importance, considering that it is extremely large in magnitude; absolutely and comparatively.[4] This paper is also complementary to Choukhmane et al. (2016), which explores the same age-saving profile using the One-Child Policy of China. Although the mechanisms seem to resemble each other, our work is differentiated from theirs in that we focus on different types of transfers. Choukhmane et al. (2016) study the educational transfer and human capital accumulation, while we study the housing transfer.

The rest of the paper is organized as follows. Section 2.2 describes the data used in this paper. Sections 2.3 and 2.4 display the direct reduced-form analyses to test the altruism mechanism and credit-constraint mechanism. Section **??** concludes.

2.2 Data and Stylized Facts

Based on various aggregate and household level data sources from China and other countries, this section provides the stylized facts which motivate this study.

First, we display the camel-shaped life-cycle saving rates of Chinese households. We provide evidence that this pattern is robust to various sources of data sets, after tackling measurement error issues. Second, we note the importance of intergenerational transfers related to housing, in absolute and relative terms: young and elderly households receive net transfers while middle-aged households give away transfers. Finally, we show that more than 71.3% of households leave their

[3]See Choukhmane et al. (2016)

[4]The elaborate statistical evidence is provided in Section 2.2.

families of origin and start their own families, at around the age of 25–35. After that, most g on to buy houses for their new families. These findings provide the motivation for this model and the reduced form analyses in the following sections.

2.2.1 Data Description

In this section, we describe the data sets used in the analysis. The data are drawn from two sources: the China Household Finance Survey (CHFS) and the China Family Panel Studies (CFPS). We use the CHFS to estimate model parameters, life-cycle saving rates and to conduct counterfactual analyses. We use the CFPS to exploit the exogenous deaths of adult children as a natural experiment, the exogenous allocation of military cadets to different cities and the accessibility of Client Express Loans (CEL).

The CHFS contains longitudinal information on a representative sample of Chinese individuals and families. It launched nation-wide surveys in 2011, 2013 and 2015, however, only the data from 2011 is available. CHFS collects information on a sample of approximately 8,000 households and 30,000 individuals in 25 provinces. In the data, different categories of financial assets and debts are available, plus information on historical intergenerational transfers of wealth. This allows us to estimate the life-cycle saving rates that depend on previous transfers.

The CFPS started in 2010, collecting information on a sample of approximately 15,000 households in 28 provinces. In the following years, 2012 and 2014, both the original sample families and their splitoffs (children moving out of the parental household) were followed; in fact, it is possible to track an individual across families. This essential feature of the survey makes the data suitable for the reduced-form analysis in this paper. It also contains detailed information about the accidental deaths of individuals which serves as a natural experiment in order to identify the effects of altruism on parents' saving rates. Additionally, it also includes individuals who graduate from military academies and the accessibility of Client Express Loans. Altogether this information forms the basis of the later empirical analysis in which we provide direct evidence of the altruism channel and the credit constraint channel.

In both data sets, we apply the same standard criteria when constructing the sample. First, we restrict the sample to household heads aged between 20 and 80, which are the groups generating or receiving transfers. Second, we exclude the observations with top coded annual earnings and we winsorize the earning variable at the 99^{th} percentile to minimize the bias caused by outliers. Third, we drop all entries with missing information in transfers and housing. Therefore, we end up with 7,028 households in CHFS and 13,719 households in CFPS.

2.3 Effects of Altruism on Saving Rates: Natural Experiment of Loss of Children

In this section, we test the altruism channel which implies that saving rates of parents decrease in relation to the altruism towards their children. There are two obstacles to implementing this test. The first difficulty is to measure altruism, which stems from its psychological nature. The past literature has developed the "dictator" games (see Hoffman et al. (1996) and Eckel and Grossman (1996)), or experiments that present subjects with situations in which they can exhibit altruism (see Andreoni and Miller (2002)). However, this experimental method is not applicable in our case. The second issue is endogeneity, whereby altruism may be correlated with unobserved characteristics that also affect the saving rates of parents. In this paper, we circumvent both problems by exploiting the exogenous deaths of children as a natural experiment.

The China Family Panel Study (CFPS) provides us with detailed information about children's accidental deaths. The last row in Table 2.1 shows that 6.32% of parents lost their adult children and do not have any more children up to the survey year.[5] These lost children are mostly adult children and the parents have exceeded the age for procreating. Hence, their altruism disappears with the lost child. More importantly, the accidents are orthogonal to the characteristics of parents.[6] Therefore, parents who accidentally lost children have exogenous variation of altruism compared to other parents.

These households form our treatment group,[7] with the control group being all the other middle-aged households.[8]

[5]The yearly accidental death rate calculated from our data set is $4.71 * 10^{-4}$. The death rate released by NBSOC in the Sixth Natioinal Population Census of the PRC (2010) is $3.27 * 10^{-4}$. As a benchmark, the death rate for the United States released by National Bureau of Labor (NBL) in 2010 is $2.19 * 10^{-4}$. This number is higher in China than in US for two main reasons. First, "One Child Policy" in China prohibits families to have more than one child. When their only child dies, the wife might has exceeded the childbearing age. Second, adoptions are relatively rare in China. In our data set, we observe less than 10 adoption cases out of more than 8,000 households. An underdeveloped pension system is one of the main reasons for leading to this low adoption rate, as the lack of a pension or a social security system means that children are raised partly as sources of old-age support in Chinese norms (*"Yang Er Fang Lao"*). Trust between children and parents is important in order to enforce this "invisible contract", which may lead to Chinese parents being less willing to adopt children.

[6]In Appendix .5.2, I provide balancing test for the treatment group and control group.

[7]The third row of Panel A in Table 2.1 shows that 8.21% middle-aged parents lost their children but have children up to the survey year. Because they give birth to other children or adopt children after the death shock. Thus, we do not focus on this group as the treatment group, because the death shocks on them are vague.

[8]In Appendix .5.2, I test with different treatment and control groups as a robustness check.

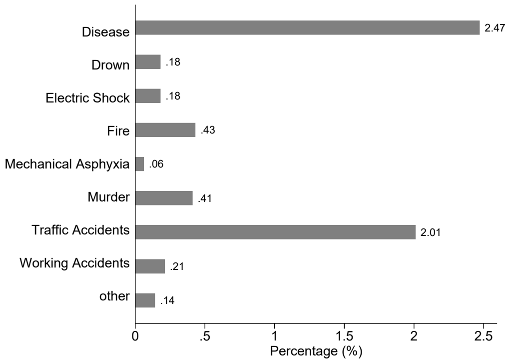


Figure 2.1: Causes of Children's Death

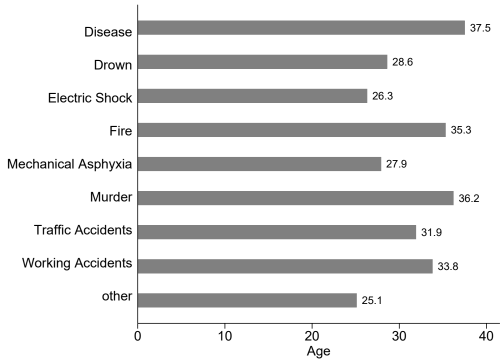


Figure 2.2: Average Ages of Children's Death

Notes: Data source: CFPS (2014). The left panel represents the proportion of children dead out of different reasons. The right panel displays the age of children when they died. Perinatal Mortality (PNM) are excluded, because no transfers are made to new born babies.

Table 2.1: Middle-aged Households With and Without Children

Types of Middle-aged Households	Percentage	No. of Children
Panel A: Have Children (up to survey year)	90.12%	1.36
- Never lost children	83.91%	1.39
- Lost children	8.21%	1.21
1. Family connection break	3.10%	1.05
2. Sending children to relatives	1.79%	1.25
3. Accidents	3.32%	1.27
Panel B: Have No Children (up to survey year)	9.88%	0
- Never give birth to children	2.79%	
- Lost children	7.09%	
1. Family connection break	0.23%	
2. Sending children to relatives	0.54%	
3. Accidents	6.32%	

Note: Data source: CFPS (2008-2014). Restricted sample of middle-aged household heads whose ages range from 40 to 60. Perinatal Mortality (PNM) are excluded, because no transfers are made to new born babies.

Next I perform the following main regression on household i at year t:

$$s_{i,t} = \alpha + \beta_1 \cdot \mathbb{1}_{Accd} + \beta_2 \cdot X_{i,t} + \beta_3 \cdot *Z_i + FE_{city} + FE_{county} + FE_{industry} + \epsilon_{i,t}, \tag{2.1}$$

where $s_{i,t}$ is household i's saving rate in period t. $\mathbb{1}_{Accd}$ refers to whether or not household i accidentally lost their children. $X_{i,t}$ and Z_i are a set of control variables which capture different characteristics of household i. $X_{i,t}$ is time-variant and Z_i is time-invariant.[9] FE_{city}, FE_{county}, and $FE_{industry}$ capture the fixed effects of people living in various cities, counties, and working in different industries. Therefore, in this regression, we compare the saving rates of people who are similar in these characteristics, with the only exogenous difference being the loss of their children. This difference is estimated by the coefficient β_1.

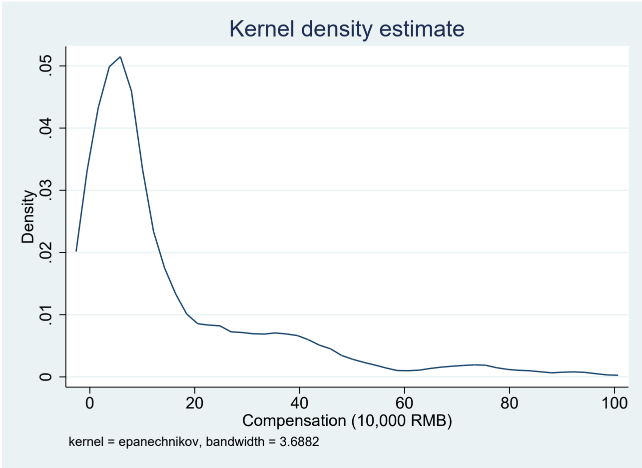
In Table 2.2, we compare saving rates of two groups.[10] Column (1) denotes that in general, the age-saving profile is camel-shaped because the coefficient of age-square is positive. However, when we focus on households who have lost their children, the coefficient moves from 0.003 to -0.002 (in Column (3)). This implies that non-altruistic parents display a hump-shaped age-saving profile, which is in line with the theoretical predictions.

Columns (2)-(6) show the differences between two groups of parents. We observe in Column (2) that households without children have savings rate 12.4% higher than households with children. Each additional child reduces the savings rate by around 4.2%. Moving right from column (2), all coefficients of the non-altruistic parents are significant. On average, there is a gap of around 12% in saving rates between altruistic and non-altruistic parents.

In Column (4)-(6), we add three more cross terms. $DeathAge^{Chd}$ is the age of the adult children when they died. $\mathbb{1}_{DeathAge^{Chd}>25}$ is the indicator of whether the children died later than age 25. $\mathbb{1}_{Deathfamily^{Chd}}$ captures whether the children themselves had families when they died. These three variables aim to capture the probability that transfers may have taken place. Regarding parents whose children died at an older age, their saving rates are smaller, *ceteris paribus*, and dropped because they made some level of transfer to their children. The biggest drop is 8.4% observed in Column (6), in which the children already had their own families when they died. Thus, for the parents whose child died and who already had their own family, there is no difference compared

[9] Z_i includes gender, ethnic group, *"Hukou"*, education level, number of children. X_{it} includes marriage status, health condition, age, income, industry, whether working in state-owned-enterprise (SOE), whether retired, social security, education and income of their parents, income and education of children, age of children.

[10] The random effects model is used instead of fixed effects model because this test focuses on difference across households instead of across time which could be almost negligible.



Data source: CHFS.

Figure 2.3: Distribution of Housing Compensation

with another parent who did not lose their child.

Next we display the same regression results using the CFPS data set and the simulated data from the counterfactual analyses. Recall that in Section 1.4.4, the counterfactual analyses mimic the reduced form analyses. Here, we regress the simulated saving rates of parents who lost their children on the same characteristics included in regression 2.1. Then we compare the results with reduced form results to quantitatively gauge how the model matches the reduced form evidence. Columns (1)-(3) in Table 2.3 are the same as Columns (1)-(3) in Table 2.2. Columns (4)-(6) display the results of running the same regression as in the first three columns while using simulated data, respectively. The estimation from the CFPS data and the simulated data are decidedly close in magnitude and significance. This implies that our OLG model in Section 17 quantitatively matches the reduced form evidence.

2.3.1 Relocation and Housing Windfall

There are 935 (12.8%) households in CHFS data set who have experienced housing demolition or relocation. And 7.33% received financial compensation from the government. Usually, the compensation is much larger in amount than the value of the demolished or relocated house.

To summarize, in this section, we test the altruism channel by exploiting the accidental loss of children as a natural experiment. We find that non-altruistic parents have saving rates around 11% higher than altruistic parents. We find that within this group of non-altruistic parents, the later they lost their children, the higher their saving rates, as they had already generated a transfer to their

Table 2.2: Effects of Altruism on Saving Rates

Dependent Variable: Saving Rates of Parents (Age: 40-60)						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{Accd}$		0.124***	0.117***	0.118***	0.121***	0.119***
		(0.031)	(0.031)	(0.032)	(0.031)	(0.029)
$\mathbb{1}_{Accd} \times Age^2_{Prt}$			-0.002**			
			(0.001)			
$\mathbb{1}_{Accd} \times DeathAge^{Chd}$				-0.023**		
				(0.011)		
$\mathbb{1}_{Accd} \times \mathbb{1}_{DeathAge^{Chd}>25}$					-0.067***	
					(0.027)	
$\mathbb{1}_{Accd} \times \mathbb{1}_{Deathfamily^{Chd}}$						-0.084***
						(0.032)
$DeathAge^{Chd}$				0.002		
				(0.009)		
$\mathbb{1}_{DeathAge^{Chd}>25}$					0.003	
					(0.007)	
$\mathbb{1}_{Deathfamily^{Chd}}$						0.004
						(0.006)
Age^2_{Prt}	0.003**	0.002	0.002	0.002	0.002	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age_{Prt}	-0.042**	-0.045**	-0.043**	-0.042**	-0.042**	-0.040*
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.21)
$Log(Income^{Prt})$	0.037***	0.039***	0.037***	0.038***	0.040***	0.041***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)
Number of Children	-0.041**	-0.042**	-0.041**	-0.042**	-0.042**	-0.042**
	(0.020)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)
City FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Year × City	YES	YES	YES	YES	YES	YES
Year × Industry	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES
R-squared	0.1796	0.181	0.192	0.189	0.201	0.200
Sample size	6,625	6,625	6,625	6,625	6,625	6,625

Notes: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60 and where parent-children pair information is complete. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other controls in all regression include: gender of households head, ethnic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether participate in social security plans.

Table 2.3: Effects of Altruism on Saving Rates: Reduced Form regression and Simulated Data Regression

Dependent Variable: Saving Rates of Parents						
	Reduced-form Regression			Simulated Data Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{Accd}$		0.124***	0.117***		0.104***	0.107***
		(0.031)	(0.031)		(0.033)	(0.034)
$\mathbb{1}_{Accd} \times Age^2_{Prt}$			-0.002**			-0.004**
			(0.001)			(0.002)
Age^2_{Prt}	0.003**	0.002	0.002	0.005**	0.003	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Age_{Prt}	-0.042**	-0.045**	-0.043**	-0.039**	-0.040***	-0.040***
	(0.021)	(0.022)	(0.022)	(0.017)	(0.018)	(0.018)
$Log(Income^{Prt})$	0.037***	0.039***	0.037***	0.035**	0.034**	0.034**
	(0.017)	(0.017)	(0.018)	(0.012)	(0.012)	(0.011)
Number of Children	-0.041**	-0.042**	-0.041**			
	(0.020)	(0.021)	(0.022)			
City FE	YES	YES	YES	-	-	-
County FE	YES	YES	YES	-	-	-
Industry FE	YES	YES	YES	-	-	-
Year FE	YES	YES	YES	-	-	-
Year × City	YES	YES	YES	-	-	-
Year × Industry	YES	YES	YES	-	-	-
Other Controls	YES	YES	YES	-	-	-
R-squared	0.179	0.181	0.192	0.812	0.832	0.878
Sample size	6,625	6,625	6,625	11,784	11,784	11,784

Note: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60 and where the parent-children pair information is complete. In Column (1)-(3), other controls include: gender of households head, ethnic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether they participate in social security plans. In Column (5)-(7), the right hand side variables include only the indicator or whether hit by the shock, age, age-square and income. Because all the other characteristics are the same by design, see Section 1.4.4. R-squares are high because there is relatively less error from simulated data compared to real data. Sample size is around twice of the reduced-form regression, because we launch the counterfactual experiment on each of middle-aged household in the data. Robust standard errors are in the parentheses. *** stands for $p < 0.01$, ** stands for $p < 0.05$, * stands for $p < 0.1$.

(lost) children.

2.4 The Credit Constraint Channel and Random Allocation of Military Cadets

In this section, we test the credit constraint channel using two mechanisms: access to mortgage loans and housing prices. As discussed in Section 1.3, tighter credit constraints or higher housing prices lead to lower saving rates of parents, *ceteris paribus*. Using cross-section variation in the implementation of the Client Express Loan (CEL) and average housing prices, we compare the saving rates of parents with children living in different cities. However, children's city choices may be correlated with unobserved family characteristics which also affect parents' saving rates. To tackle this endogeneity issue, we exploit the exogenous allocation of military cadets in China as randomized controlled trials (RCT) for both mechanisms. Before testing each mechanism, we introduce the military cadets data set and explain why they circumvent the endogeneity issue.

2.4.1 Military Cadets

There are 5.31% (c.a. 873) households who graduate from military academies in the CFPS data.[11] Table 2.4 represents the characteristics of military households against the non-military households. There are two significant differences between these two groups of households.[12] First, the sex ratio is different. Because the recruitment of military academies is inclined towards male students, a higher proportion of males are involved in the military sample than in the non-military sample. Second, more than 70% of the military cadets come from families with a military background, while the ratio is less than 30% in the non-military sample. We control for both characteristics when running the regressions in order to test the mechanisms of mortgage access and housing prices.

After graduation, military cadets are randomly allocated to different cities by the People's Liberation Army so as to become military officers or civilians. The decision to assign jobs is highly centralized within the P.L.A. General Political Division, and also highly demand-driven. This feature leads to the location of military cadets being exogenous from the characteristics of their parents.

In order to test whether or not location choices for military graduates are exogenous from their individual and family characteristics, we run a multinomial logit (MNL) model, following Equation

[11] There are in total 45 military academies in China. Their distribution across provinces can be seen in Figure 31.

[12] The difference of education level between the military and non-military sample stems from the fact that all of the military cadets have post-secondary education while all non-military households do not.

Table 2.4: Military and Non-military Households

Variable	Military	Non-military	Difference	t-stats
Panel A: Individual Characteristics				
Age	43.46	40.53	2.93	1.28
Han	0.39	0.41	-0.04	1.67
Male	0.73	0.48	0.02	2.74**
Urban	0.43	0.41	0.02	0.76
Number of Siblings	1.43	1.58	-0.15	-0.96
Years of Education	17.38	11.93	5.45	4.27***
Income	15,314.71	15,036.11	278.60	1.17
Panel B: Parents Characteristics				
Yeas of Education	12.71	11.98	0.73	1.21
Income	8,920.49	8,212.59	707.90	1.44
Military Backgrounds	0.72	0.24	0.48	4.83***
Assets	30,879.25	35,268.96	-4,389.71	-1.28
Liabilities	919.56	1215.33	-295.76	-0.87
Average Consumption	10,149.32	11,851.95	-1,702.63	-1.51

Note: Data source: CFPS (2010, 2012, 2014). Individual characteristics refer to characteristics of the military cadet whether he/she is the head of family or not. Number of siblings exceed 1 because we include households living in rural area. Income is defined as the sum of net transfers, income from employment and capital returns. Assets refer to the sum of demand deposits, time deposits, stocks, bonds, funds, derivatives. Liabilities involve the same categories of financial assets.

2.2:

$$City_i^{Tier} = \alpha + \beta_1 \cdot \cdot Age_i^{Chd} + \beta_2 \cdot Age_i^{Prt} + \beta_3 \cdot Gender_i^{Chd} + \beta_4 \cdot Income_i^{Chd} + \beta_5 \cdot SavingRate_i^{Prt} + \epsilon_i. \tag{2.2}$$

Results are displayed in Table 2.5. Column (1) displays the results for the entire sample, and Column (2) displays the results restricted to the households that graduate from the military universities. All observations that are significantly correlated with city choices for the non-military households become insignificant for military households. Therefore, location choices are orthogonal to individual and family characteristics as displayed in Table 2.5. What is more, Pseudo R-square and Log Likelihood are both small (see Column (2)). This evidence suggests that individual and family characteristics do not provide an explanation for the location choices of military students.

2.4.2 Access to Mortgage: Client Express Loans

In this section, we test the mechanism of the mortgage loan: if children have more access to mortgage loans, their parents have higher saving rates. We tackle the endogeneity issue by focusing on the military cadets sample introduced above. To explore the cross-city variation, we introduce the "Client Express (in Chinese, Zhi Ke) Loan" (CEL).[13]

CEL was first implemented by the Bank of China (BOC) in 2007 in three cities: Beijing, Shanghai and Guangzhou. The CEL benefits the borrowers by providing the eligible clients with the opportunity to apply for loans amounting to a full house payment. In reward for this full payment, buyers enjoy a 5%-7% discount from their real estate companies.

After success in Beijing, Shanghai and Guangzhou,[14] CEL quickly spread from these three cities to another seven cities in 2008. Up until 2010, the CEL was available in 27 cities in any of the BOC local branches. In the wake of CEL's success within the BOC, other banks have also created similar home mortgage products, such as the Agricultural Bank of China (ABC), the Industrial and Commercial Bank of China (ICBC), and the China Construction Bank (CCB), to name a few. The housing mortgage innovation surged to its peak around 2011; see Figure 2.4. At the end of 2010, there were a total of 91 banks/branches that created innovative mortgage loan products, while at the end of 2012, this number increased to 257, which is equal to a coverage of 67.3% of mortgage

[13] We do not use difference in down payment ratio because China has nationwide down payment ratio for house purchasing. It is announced as 30% for the first house and 20% for the second house, by the People's Bank of China (BPoC) and the China Banking Regulatory Commission (CBRC) in their issue "Notifications on Discrimination on Housing Credit Policy", starting from June 1st, 2006. The notification is available in Chinese: *Notifications on Discrimination on Housing Credit Policy*.

[14] In the BOC's annual report in 2010, the CEL's contribution to housing mortgage transaction growth is 32.78%

Table 2.5: Multinomial Logit Regression: City Choices

Dependent variable: City Choices			
		(1)	(2)
		All Households	Military Cadets
Tier I City	Age^{Chd}	-0.007	-0.005
		(0.005)	(0.003)
	Age^{Prt}	0.007	0.007
		(0.005)	(0.006)
	$Gender^{Chd}$	-1.71*	-1.33
		(0.80)	(0.83)
	$Income^{Chd}$	2.33***	0.12
		(0.123)	(0.092)
	$SavingRate^{Prt}$	0.057***	0.013
		(0.023)	(0.012)
	Constant	-0.78**	-2.15***
		(0.34)	(0.19)
Tier II City	Age^{Chd}	-0.07	-0.007
		(0.008)	(0.006)
	Age^{Prt}	0.006*	0.004
		(0.003)	(0.003)
	$Gender^{Chd}$	-1.04	-1.07
		(1.31)	(1.21)
	$Income^{Chd}$	4.78***	2.92
		(1.23)	(0.54)
	$SavingRate^{Prt}$	0.036***	0.015
		(0.014)	(0.013)
	Constant	-1.27***	-2.31***
		(0.32)	(0.12)
$PseudoR^2$		0.21	0.04
Log Likelihood		-3531.7	-10469.34
Sample Size		6,625	753

Note: Data source is CFPS (2010, 2012, 2014). Tier III city is chosen as the base outcome for both regressions. The probability of choosing Tier I city is calculated as: $Pr(City = I) = \frac{e^{2.33-0.78}}{1+e^{2.33-0.78}+e^{4.78-1.27}} = 0.1202$. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

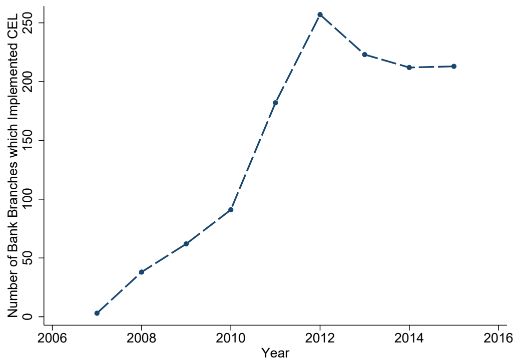


Figure 2.4: CEL Prevalence in China, 2007-2014

Notes: Data source: annual reports of commercial banks in China (2007 to 2014). The commercial banks include: Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, China Construction Bank, Bank of Communications, Postal Savings Bank of China, China Everbright Bank, China Minsheng Bank, China Merchants Bank, Citic Bank, Hua Xia Bank, Shanghai Pudong Development Bank, Ping An Bank, China Guangfa Bank, Industrial Bank, China Zheshang Bank. These banks altogether capture more than 80% of Chinese commercial banks in terms of Total Enterprise Value (TEV).

loans taking place under a specific kind of loan package. After that time, it remained close to the peak number for the subsequent two years before it declined to 212 in 2014.

Therefore, we are able to exploit cross-city and over-time variations to identify the effect of children's mortgage access on parents' saving rates. Furthermore, a local bank's decision of whether or not to carry out this regulation may be regarded as exogenous from individual households saving rates.[15] Apart from these issues, the most important feature of the CEL leading to it being the most preferential treatment for this study is that it only applies to households that purchase a house within the same city as their loaning bank. This rules out the possibility of arbitrage across cities. In this way, the information of a household's residential location leads directly to whether or not they are eligible for the CEL package.

A difference-in-difference (DID) method is used to estimate the impact of the CEL on the saving rates of the middle-aged households. The following regression is performed for a household i living in city j at period t:

$$\begin{aligned} s_{it}^{Prt} &= \alpha + \beta_1 \cdot \mathbb{1}_{jt}^{CEL} + \beta_2 \cdot \mathbb{1}_{jt}^{CEL} \times Discount_{ij} + \beta_3 \cdot City_{I}^{Prt} + \beta_4 \cdot City_{II}^{Prt} \\ &+ \beta_5 \cdot X_{it} + \beta_6 \cdot *Z_i + FE_{city} + FE_{county} + FE_{industry} + \epsilon_{ijt} \end{aligned} \tag{2.3}$$

where s_{it}^{Prt} is the saving rate of parents, $\mathbb{1}_{ijt}^{CEL}$ captures whether or not city j has implemented CEL

[15]Whether or not applicants get approved by the bank can be an endogenous decision, depending on households asset holdings, income level. Fortunately, the information about underwriting are available in the CFPS data. So I include them as control variables to avoid potential endogeneity issue.

in year t. $Discount_{ij}$ represents the favorable discount ratio elaborated in CEL contracts. This ratio varies across cities.

The results are displayed in Table 2.6. Here we display results for the military and non-military sample with estimations for the two groups close in terms of quantity. If children live in cities which have implemented CEL, their parents have saving rates around 8% higher than other parents, *ceteris paribus*. If we focus on these parents, their saving rates change with the discount of CEL. One percent of increase in discount leads to around 2% of increase in parents' saving rates.

Table 2.6: Effects of CEL Accessibility on Saving Rates of Parents

Dependent variable: Saving rates of Parents	Non-military Sample		Military Sample	
	(1)	(2)	(1)	(2)
$\mathbb{1}^{CEL}$	0.082***	0.082***	0.080***	0.081***
	(0.019)	(0.021)	(0.020)	(0.021)
$\mathbb{1}^{CEL} \times$ Discount		2.07***		2.03***
		(0.59)		(0.57)
Discount		0.008		0.007
		(0.012)		(0.011)
$Log(Income^{Prt})$	0.037**	0.038***	0.038**	0.037**
	(0.018)	(0.018)	(0.018)	(0.017)
Number of Children	-0.041**	-0.042**	-0.041**	-0.040**
	(0.022)	(0.021)	(0.020)	(0.020)
$City_I^{Prt}$	0.017	0.015	0.016	0.015
	(0.035)	(0.032)	(0.034)	(0.033)
$City_{II}^{Prt}$	0.013	0.014	0.014	0.013
	(0.032)	(0.034)	(0.031)	(0.032)
City FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Year × Industry FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES
R-squared	0.198	0.213	0.210	0.217

Notes: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other controls in all regression include: gender of households head, ethic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether participate in social securities.

2.4.3 Mechanism of Housing Prices

In this section, we test the housing price mechanism. Parents whose children live in cities with higher housing prices have lower saving rates, *ceteris paribus*. Again, we use the military cadets sample to solve the endogeneity issue related with to choices.

Housing prices have experienced a sharp increase in the recent decade, with a rich variation in housing prices across cities. Figure 2.5 represents the average Housing Price (P_H) and Housing Price to Income Ratio (P_H/I) from 2001 to 2015 in China. We observe that both P_H and P_H/I started to accelerate after 2005 when the privatization of the housing market accelerated. The average housing price to income ratio reached 11.97 in 2014, compared to 4.71 in US, and 3.31 in OECD countries, in the same year.

Figure 2.5: Housing Prices and Housing Price to Income Ratio

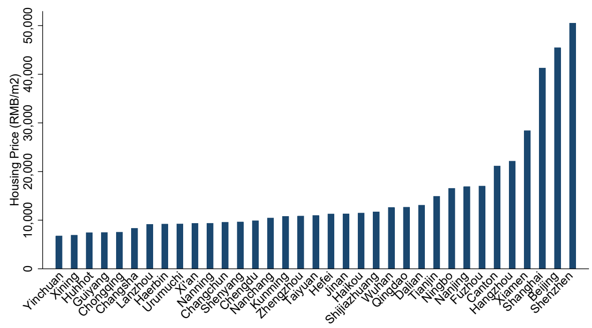


Figure 2.6: Housing Prices across Cities, 2014

Notes: Data source: Chinese Statistics Yearbook (2000-2014). Housing prices is measured by the Average Selling Price (ASP) of residential real estate. Housing price to income ratio: ASP of residential real estate over average total annual income of households. Total income is defined as the sum of transfers plus incomes from employment, pensions and asset returns.

Moreover, the climbing of housing prices is asymmetric across cities. Figure 2.6 represents a cross-city pattern of housing prices. We observe that Shenzhen, Beijing and Shanghai take the lead in housing prices. Following a descending order of housing prices, I divide all the 35 cities into three groups: high prices group, medium prices group, and low prices group.[16] The average housing price of high prices group is approximately twice that of the prices in the medium group, and four times that of the prices in the low group.

Before presenting the reduced-form results, we display some descriptive evidence. Figure 2.7 displays age-saving profiles for households living in the three categories of cities. We observe that parents whose children live in high prices category have a more pronounced "camel-shaped" pattern than the other two categories. This partly validates our supposition that the trough on

[16]As displayed in Figure 2.6, high prices category includes Beijing, Shanghai, and Shenzhen; medium price category includes Xiamen, Hangzhou and GuangzhouFuzhou, low price category includes Taiyuan, Tianjin, Hangzhou, Nanjing, Guangzhou, Haikou, Zhengzhou, Dalian, Urumuchi, Ningbo, Nanchang, Hefei, Shijiazhuang, Nanning, CHongqing, Wuhan, Lanzhou, Changchun, Haerbin, Kunming, Xi'an, Jinan, Chengdu, Qingdao, Guiyang, Shenyang, Hohhot, Y-inchuan, and Changsha.

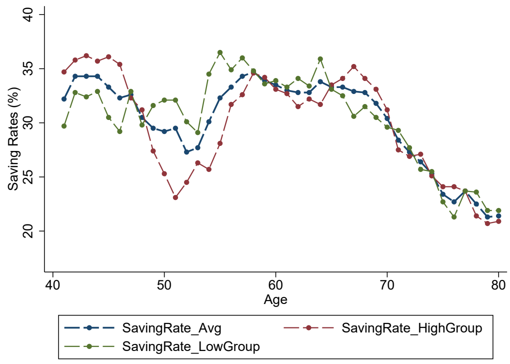


Figure 2.7: Age-saving Pattern

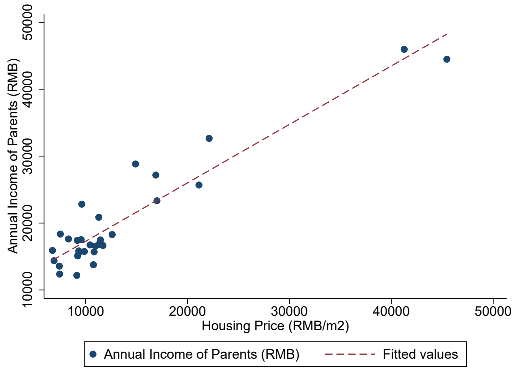


Figure 2.8: Parents' Income and Housing Prices in Children's Cities

Notes: Data source: CFPS (2014). The sample is restricted to parents whose age range from 40-80, and children are military cadets. In the left panel, "$High_Group$" denotes high housing prices category of cities, and "Low_Group" denotes low housing prices category of cities.

middle-aged households' saving rates stems from the intergenerational transfers related to house purchasing.[17] Figure 2.8 displays the potential endogeneity issue discussed in the previous section. There is a positive relationship between parents' income and children's city-level housing prices. This leads to an upward bias in our estimation.

Then we estimate difference in parents' saving rates following the regression equation:

$$\begin{aligned} s_{it}^{Prt} &= \alpha + \beta_1 \cdot City_H^{Prt} + \beta_2 \cdot City_M^{Prt} + \beta_3 \cdot \mathbf{City_H^{Chd}} + \beta_4 \cdot \mathbf{City_M^{Chd}} \\ &+ \beta_5 \cdot X_{it} + \beta_6 \cdot *Z_i + FE_{city} + FE_{county} + FE_{industry} + \epsilon_{i,t} \end{aligned} \tag{2.4}$$

where $City^{Prt}$ and $City^{Chd}$ are locations of parents and children, respectively. We only include dummies for the high prices category and the medium prices category, and the low prices category is used as the benchmark group.

In Table 2.7, the first three columns present results of the military sample and the last three columns present results of the non-military sample. In Column (1), children's locations have significant a effect on their parents' saving rates, while parents' locations do not. When comparing children living in high price cities and low price cities, their parents have a gap of 11.2% in saving rates. When comparing children living in medium price cities and low price cities, their parents have a smaller gap of 9.3%. This is consistent with the theory predictions that higher housing prices for children leads to a lower saving rate for parents. In Column (3), adding housing prices to the regression leads to insignificant coefficients of children's locations. This implies that a large propor-

[17]Migration among different cities can be seen in Appendix .6.

Table 2.7: Effects of Housing Price on Saving Rates of Parents

Dependent variable: Saving rates of Parents	Military Sample			Non-Military Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
$Log(HousingPrice)^{City}$			-0.131***			-0.112***
			(0.036)			(0.037)
$City_H^{Chd}$	-0.112***	-0.110***		-0.095***	-0.091***	
	(0.033)	(0.032)		(0.033)	(0.032)	
$City_M^{Chd}$	-0.093***	-0.092***		-0.078***	-0.076***	
	(0.031)	(0.030)		(0.031)	(0.030)	
$City_H^{Chd} \times Gender$		-0.051***			-0.047***	
		(0.017)			(0.013)	
$City_M^{Chd} \times Gender$		-0.037***			-0.038***	
		(0.013)			(0.013)	
$City_H^{Prt}$	0.013		0.016	0.015		0.017
	(0.038)		(0.039)	(0.043)		(0.035)
$City_M^{Prt}$	0.013		0.013	0.012		0.013
	(0.036)		(0.031)	(0.037)		(0.032)
$Gender_{Chd}$		-0.041***	-0.037***		-0.037***	-0.038***
		(0.012)	(0.014)		(0.013)	(0.014)
Age_{Prt}	-0.039**	-0.040**	-0.040**	-0.041**	-0.039*	-0.041*
	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
$Log(Income^{Prt})$	0.038***	0.039***	0.038***	0.039***	0.039**	0.040***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
$Number_{Chd}$	-0.040**	-0.041**	-0.042**	-0.042**	-0.041**	-0.043**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
City FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Year × City	YES	YES	YES	YES	YES	YES
Year × Industry	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES
R-squared	0.166	0.191	0.183	0.177	0.198	0.185
Sample size	753	753	753	1,623	1,623	1,623

Notes: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60 and parent-children pair information is complete. $City_H$ stands for high prices cities, and $City_M$ stands for medium prices cities. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other controls in all regression include: gender of households head, ethic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether participate in social securities.

tion of the effects related to location can be captured using housing prices. This further validates the hypothesis that the differences in parents' saving rates stem from the differences in housing prices across cities. Finally, the results of the non-military sample in the last three columns are similar to the military sample, with a slight upward bias of 1.5% for children's locations. This bias could result from the positive relationship between children's locations and unobserved characteristics affecting parents' savings or incomes. In spite of this small upward bias, the effects of children's locations on parents' saving rates are still large in magnitude and significantly different from zero.

Also, in this table we test the joint effect of the altruism channel and the credit constraint channel by using the cross term $City^{Chd} \times Gender$. This terms measures the gap of saving rates between parents with boys and with girls, given the tightness of borrowing constraints are the same. The "Missing Women of China", coined by Amartya Sen, indicates that the sex ration is distorted in which the number of males far outweighs the number of females (see Figure 2.8 and Sen (1990), Sen (1992)). Guiding by this, the gender can be used as a proxy to measure the degree of altruism: parents display more altruism to boys than to girls. In Table 2.7, parents with boys have saving rates of around 4% lower than parents with girls, *ceteris paribus*. And the cross term of $City^{Chd} \times Gender$ display a difference of around 5% between high prices cities and low prices cities, and a difference of around 3% between medium prices cities and low prices cities.

In this section, we test the credit constraint channel using two mechanisms: the access to mortgage and housing prices. We exploit the random allocation of military cadets in China to solve the endogeneity issue related to children's location choices. We find that access to a Client Express Loan (CEL) leads to a drop of around 8% in parents saving rates. Also, comparing children living in high price cities and low price cities, we find a difference of around 10% in their parents' saving rates. Together, these two tests altogether validate the credit constraint channel that a tighter borrowing constraint and higher housing prices lead to lower saving rates for middle-aged parents.

2.5 Conclusion

In this paper, we investigate the role of intergenerational transfers in explaining the "camel-shaped" age-saving profile of Chinese households. In a quantitative overlapping generations (OLG) model, saving rates are linked with the altruism of parents and the credit constraints of their children, through intergenerational transfers. Two channels are important: the altruism channel and the credit constraint channel. The altruism channel implies that the saving rates of middle-aged

Table 2.8: Effects of Housing Price on Saving Rates of Parents

Dependent variable: Saving rates of Parents *(Restricted to Military Sample)*					
	Reduced-form Regression			Simulated data Regression	
	(1)	(2)	(3)	(4)	(5)
$Log(HousingPrice)^{City}$			-0.131***		-0.147***
			(0.036)		(0.036)
$City_H^{Chd}$	-0.112***	-0.110***		-0.139***	
	(0.033)	(0.032)		(0.033)	
$City_M^{Chd}$	-0.093***	-0.092***		-0.087***	
	(0.031)	(0.030)		(0.031)	
$City_H^{Chd} \times Gender$		-0.051***			
		(0.017)			
$City_M^{Chd} \times Gender$		-0.037***			
		(0.013)			
$City_H^{Prt}$	0.013		0.016		
	(0.038)		(0.039)		
$City_M^{Prt}$	0.013		0.013		
	(0.036)		(0.031)		
$Gender_{Chd}$		-0.041***	-0.037***		
		(0.012)	(0.014)		
Age_{Prt}	-0.039**	-0.040**	-0.040**	-0.039**	-0.040*
	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)
$Log(Income^{Prt})$	0.038***	0.039***	0.038***	0.052***	0.051***
	(0.019)	(0.019)	(0.018)	(0.020)	(0.020)
$Number_{Chd}$	-0.040**	-0.041**	-0.042**		
	(0.020)	(0.020)	(0.020)		
City FE	YES	YES	YES	-	-
County FE	YES	YES	YES	-	-
Industry FE	YES	YES	YES	-	-
Year FE	YES	YES	YES	-	-
Year × City	YES	YES	YES	-	-
Year × Industry	YES	YES	YES	-	-
Other Controls	YES	YES	YES	-	-
R-squared	0.166	0.191	0.183	0.831	0.819
Sample size	753	753	753	753	753

Notes: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60, children who served as military cadets and parent-children pair information is complete. Column (1)-(3) display the same results as Column (1)-(3) in Table 2.7. Simulated data regression uses saving rates estimated from Section 1.5.2. $City_H$ stands for high prices cities, and $City_M$ stands for medium prices cities. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other controls in all regression include: gender of households head, ethic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether participate in social securities.

parents decline with their strength of altruism. The credit constraint channel implies that saving rates of parents decline with the tightness of their children's credit constraints on house purchasing. Next we validate the two channels using the CFPS and CHFS data sets.

Using the China Household Finance Survey data set, we calibrate/estimate model parameters and accordingly estimate the life-cycle saving rates for Chinese households. These saving rates are in line with the saving rates calculated from the data. Moreover, we launch a counterfactual experiment in which parents are shocked by the accidental deaths of their children. This mimics the natural experiment in the reduced form analysis. The counterfactual results imply that altruism towards children is essential in order to generate "camel-shaped" life-cycle saving rates.

Then, using a sample of matched parent-child pairs from the China Family Panel Studies, we test the "altruism" channel by exploiting the exogenous deaths of children as a natural experiment. We find that non-altruistic parents have saving rates of around 12% higher than altruistic parents. We also find that within these non-altruistic parents, the later they lost their children, the higher saving rates they have, as they have already generated some of their transfers to their (lost) children. Comparing the results of the reduced-form regressions and simulated data regression, we conclude that model is quantitatively consistent with the reduced-form results.

Next, we test the credit constraint channel using two mechanism: access to a mortgage and housing prices. We exploit the random allocation of military cadets in China in order to solve the endogeneity issue related to children's location choices. We find that access to the Client Express Loan (CEL) leads to a drop of around 8% in parents' saving rates. Also, when comparing children living in high price cities and low price cities, we find a difference of around 10% in their parents' saving rates. These two tests together validate the credit constraint that tighter borrowing constraint and higher housing prices lead to lower saving rates for middle-aged parents.

Chapter 3

Mergers and Acquisitions, and Its Propagation in Production Network

Abstract

This paper examines whether firm-level idiosyncratic shocks propagate in production networks. We identify idiosyncratic shocks with mergers and acquisitions (M&A). We find that M&A events impose substantial productivities and revenues gains on the target firms. These gains translate into significant output increase and spill over to their customers through input-output linkages. Surprisingly, the indirect effects of M&A on customer firms are much larger than the direct effects on target firms. This comes from the fact that M&As leads to increase of asymmetry in network structure, therefore further amplifies the firm-level shocks.

Keywords: Propagation, Network, Merger and acquisition

3.1 Introduction

Most modern macroeconomics abstracts away from network. Standard models wrap all of the intermediate processes into one representative firm. Thus, we neglect the richness of the economy's interconnections. Starting with Long and Plosser (1983), a lot of empirical studies have proved that network structure is very important in understanding the origin of aggregate fluctuations. However, the propagation of firm level shocks remains an open question, both in theory and empirics.

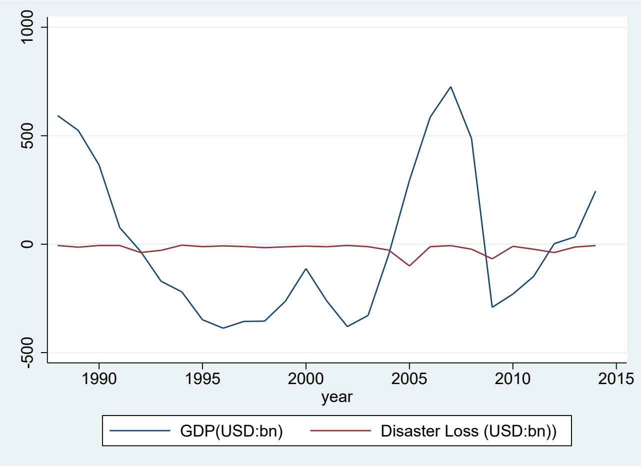
This paper studies how idiosyncratic shocks propagate to aggregate level using firm-level data. Acemoglu et al. (2012) proves theoretically, that only if there exists significant asymmetry in the roles that sectors play as suppliers to others, sizable volatility can be obtained. Sectoral asymmetry, or "influential matrix", can be calculated using input-output table. However, firm-level influential matrix is very difficult, even impossible, to calculate with available data. Then, how can we investigate propagation of firm-level shocks?

In order to answer this question, we focus on shocks that have been proved to correlate with business cycle and explore why they propagate. To identify firm level shocks, different from past literatures, we use mergers and acquisitions (M&A). There are two important reasons why we use it.

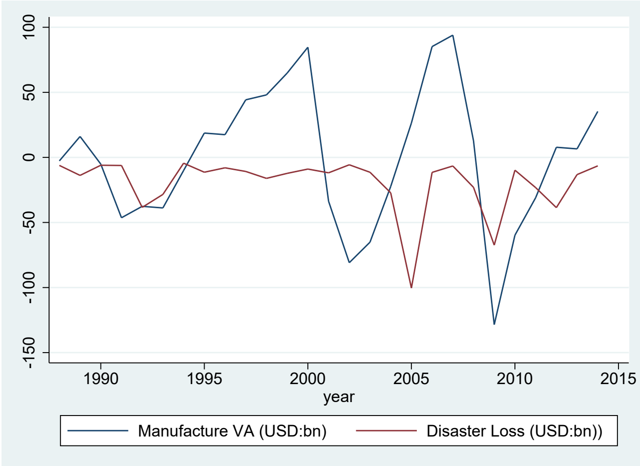
First, M&A is pro-cyclical. This validates that M&As indeed propagate.[1] Previous studies, such as Barrot and Sauvagnat (2016) and Carvalho et al. (2016), use natural disasters.[2] Natural disasters are very reliable because of its exogeneity. However, the fact that natural disaster can diffuse from supplier to customer does not mean it contributes to aggregate fluctuations. In fact, Figure 3.1 indicates that natural disasters are not correlated with business cycles.

[1]It could be the other way around which better economy situation generates more M&A events. We deal with this endogeneity issue with an instrument variable method in Section 3.4.

[2]Barrot and Sauvagnat (2016) uses natural disasters in US in recent 30 years. And Carvalho et al. (2016) uses the great East Japan Earthquake of 2011.



(a) GDP



(b) Manufacture(VA)

Notes: Data source: Natural Disaster: SHELDUS and National Weather Service of US. Value-Added of Manufacture: World Bank.

Figure 3.1: Natural Disaster and Business Cycle

Second, M&As increase the asymmetry of network structure. If M&As do not change degree distribution, they will decay along the supply chain, just like natural disasters. It can be spread, but it will die out somewhere in the network, according to Acemoglu et al. (2012). In other words, it will not cause aggregate fluctuations. How does M&A change network structure? Consider the network depicted in Figure **??**. Before M&A, the distribution of out-degree is uniform (2,2,2,2). There is no asymmetry in this network, and every firm is equally important. No shocks will propagate in this network. After M&A, two separate firms are combined into one. The distribution becomes (4,2,2). This makes the new firm far more important than the others. In this paper, we will estimate the importance of changing network structure.

Therefore, we collect firm level data on mergers and acquisitions in the past ten years using Capital IQ database.[3] According to our estimations, we find that M&A has a short-term positive effect on revenues and a prolonged positive effect on productivities of target firms. It increases firms' revenues by around 10%, and productivities by about 3%. Out of consideration on endogeneity issue, we use both difference-in-difference (DID) and instrument variable (IV) method. DID method compares the firms performances ex ante and ex post. The control group is built up by firms having M&As later than the treated group. By doing this, we avoid the potential endogeneity problem that M&A decision depends on unobserved variables of the target firms. However, the endogenous timing of M&As cannot be solved. The instrument variable is constructed as *merger arbitrage spread*.

[3] A detailed description of data set can be seen in Appendix.

Mergers trade at a discount because there always an uncertainty that a deal will break. The merger arbitrage spread captures this risk of M&A. It is correlated with M&A transactions, while independent of productivities. Productivities can only be changed through long term of reallocating assets or adopting of new technologies. The merger arbitrage spread is a short-term market reaction to the news of M&A. Therefore, they are not correlated.

We then trace the propagation of these shocks in production networks using a giant supplier-customer adjacency matrix which we calculate from Capital IQ data base. We find that almost every firm is connected in the supplier-customer network; and this network indeed has the asymmetry features mentioned in Acemoglu et al. (2012). It can be approximated by a Type-I Pareto with $\alpha = 1.8$. Here we discriminate self-M&A from supplier-M&A. The supplier-M&A refers to the M&A events happened to a firm's suppliers. Supplier-M&As are more prevalent than we expect, and of higher frequency. About 15% of firms are involved in supplier-M&As. And they have supplier-M&As happening every two years. According to our estimations, supplier-M&A increases a firm's revenues more than self-M&A by almost twice. This is very surprising if we consider that intermediate goods takes only a fraction in production function. This surprisingly large effects come from the fact that M&A combines the connections of these two firms therefore changes the distribution of "influence" of the firms. Firms involved in M&A transactions become more important because they asymmetrically supply to more customers. Therefore, the effects are amplified.

Literature and Contribution. Neoclassical theory proposes that vertical mergers may eliminate an existing inefficiency, such as double price markups in successive monopolies (Spengler (1950), Perry (1978)) or input substitution (Vernon and Daniel (1971), Schmalensee (1973), Warren-Boulton (1974)). Another neoclassical motive for vertical mergers is to prevent resale of an input in downstream industries in order to allow price discrimination across different price elasticities of demand (Katz (1987)). As an alternative to the neoclassical theory, transaction costs may lead to vertical integration if the net benefits of internal transactions are larger than those of transacting in a market. The costs of market transactions and the corresponding holdup problems increase with both uncertainty and relationship-specific investments. Thus, firms with complementary assets may merge with each other to overcome incomplete contracts (Thodes-Kropf et al. (2008).)

3.2 Model

In this section, we describe a simplistic model which highlights the main mechanisms in the empirical sections. This model is static, and there are two types of agents: consumers and firms. There are K industries in this economy, and each has a mass of N_k firms. The market is monopolistic competition, and each firm produces only one product.

3.2.1 The Household's Problem

In the economy, there is a mass of unity homogeneous households. The representative household maximizes utility:

$$U(c_1, ..., c_K) = \left(\sum_{k=1}^{K} \alpha_k^{\frac{1}{\sigma}} c_k^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where c_k represents the consumption of varieties in industry k. α_k determines households' tastes for goods from industry k. $\sigma > 0$ is the elasticity of substitution across industries. The composition good produced by industry k is given by:

$$c_k = \left(\int_{N_k} c(k,i)^{\frac{\epsilon_k - 1}{\epsilon}} di \right)^{\frac{\epsilon_k}{\epsilon_k - 1}}$$

where $c(k,i)$ is household consumption from firm i in industry k. $\epsilon_k > 1$ is the elasticity of substitution intra-industry k across firms producing different varieties. If $\epsilon_k = 1$, we have the Cobb-Douglas case. If $\epsilon = \infty$, we have the case where all varieties are perfect substitutes, and there is no product differentiation. The household budget is given by:

$$\sum_{k=1}^{K} \int_{N_k} p(k,i) c(k,i) di = wl + \sum_{k=1}^{K} \int_{N_k} \pi_{k,i} di$$

Households both earn working salaries and dividends by supplying their labor and owning the firm. We assume inelastic labor supply l, and normalize labor to be the numeraire so that $w = 1$.

3.2.2 The Firm's Problem

Firm (k,i) represents a firm i in industry k. This firm has a CES production function. It uses labor and intermediate goods as inputs. Firm (k,i) uses intermediate goods from all the firms in this economy. The production function is:

$$y(k,i) = z(k,i)\left(\gamma_k^{\frac{1}{\sigma}} l(k,i)^{\frac{\sigma-1}{\sigma}} + \sum_{s=1}^{K} \omega_{s,k}^{\frac{1}{\sigma}} m_{s,k,i}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

where $\gamma_k > 0$ gives the intensity with which firms in industry k use labor. $z(k,i)$ is productivity. $\omega_{s,k}$ is the share parameter for how intensively firms in industry k uses composite inputs from industry s. The $N \times N$ matrix of $w_{s,k}$ denoted by Ω, determines the network structure of this economy. And we will derive the influential matrix from Ω. The composite intermediate input from industry s sold to a firm i in industry k is:

$$m_{s,k,i} = \left(\int_{N_s} m_{s,j,k,i}^{\frac{\epsilon_s-1}{\epsilon_s}} dj\right)^{\frac{\epsilon_s}{\epsilon_s-1}}$$

where $m_{s,j,k,i}$ is the intermediate inputs selling from firm j in industry s to firm i in industry k. Note that elasticities ϵ_s are the same for all firms in a same industry. And elasticity σ is the same for all industries. Intensities of labor and intermediate goods, and productivities of labor are also on industry level. Therefore, we can derive the profits of firm (k,i):

$$\pi(k,i) = p(k,i)y(k,i) - \sum_{s=1}^{K} \int_{N_s} p(s,j)m(s,j,k,i)dj - wl(k,i) - f(k,i)$$

where $f(k,i)$ is the fixed cost of firm (k,i).

3.2.3 Equilibrium

Definition 2. A general equilibrium is a collection of prices $p(i,k)$, wage w, input demands $x(s,j,k,i)$, outputs $y(k,i)$, and consumption $c(k,i)$ and labor demand $l(k,i)$ such that:

1. The representative household chooses consumption to maximize utility subject to its budget constraint;

2. Each firm maximizes its profits subject to demand for its goods;

3. Markets for each good and labor clear:

$$y(k,i) = c(k,i) + \sum_{s=1}^{K} \int_{N_k} m(k,i,s,j)dj$$

$$\sum_{k=1}^{K} \int_{N_k} l(k,i)di = 1$$

The optimal consumption choice for a representative household, given goods price $p(k,i)$, is that

$$c(k,i) = \alpha_k \left(\frac{p(k,i)}{\mathbb{P}_k}\right)^{-\epsilon_k} \cdot \left(\frac{\mathbb{P}_k}{\mathbb{P}}\right)^{-\sigma} \cdot \mathbb{C} \tag{3.1}$$

where $\mathbb{P}_k = \left(\int_{N_k} p(k,i)^{1-\epsilon_k} di\right)^{\frac{1}{1-\epsilon_k}}$ is the price index of industry k, and $\mathbb{P} = \left(\sum_{k=1}^{K} \alpha_k \mathbb{P}_k^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the price index of this economy. C is the total expenditure on consumption goods.

The optimal choice for a firm (k,i) yields that:

$$p(k,i) = \frac{\tilde{\epsilon}_k}{\tilde{\epsilon}_k - 1} \cdot MC(k,i)$$

$$p(k,i) \left(\frac{\gamma_k y(k,i)}{l(k,i)}\right)^{\frac{1}{\sigma}} \cdot z(k,i)^{\frac{\sigma-1}{\sigma}} = w$$

$$p(k,i) \left(\frac{y(k,i)\omega_{s,k}}{m(s,k,i)}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{m(s,k,i)}{m(s,j,k,i)}\right)^{\frac{1}{\epsilon_s}} = p(s,j), \quad \text{for } \forall s,j$$

where $\tilde{\epsilon}_k = -\frac{\partial y(k,i)}{\partial p(k,i)} \cdot \frac{p(k,i)}{y(k,i)}$. This elasticity is constant inside industry k. Without intermediate goods, $\tilde{\epsilon}_k = \sigma$, this is the case of Dixit-Stiglitz model. And $MC(k,i)$ is the marginal cost of firm (k,i), which equals to $z(k,i)^{\frac{1}{\sigma}} \left(\gamma_k w^{1-\sigma} + \sum_{s=1}^{K} \omega_{s,k} \mathbb{P}_s^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$.

Therefore, we derive the revenues $r(k,i)$ and profits $\pi(k,i)$ for firm (k,i):

$$\begin{aligned} r(k,i) &= p(k,i)y(k,i) \\ &= \psi_k \cdot \delta_k \cdot \mathbb{P}^{\sigma} \mathbb{C} w^{1-\sigma} \end{aligned} \tag{3.2}$$

$$\pi(k,i) = \frac{\tilde{\epsilon}_k - 1}{\tilde{\epsilon}_k} r(k,i) - f(k,i) \tag{3.3}$$

where ψ_k is the supply centrality of industry k. It is the k^{-th} element of vector Ψ. And δ_k is the demand centrality of industry k. It is the k^{-th} element of vector Δ.

$$\Psi' = \alpha' \tilde{\Psi}$$

$$\Delta' = \gamma' \tilde{\Delta}$$

where $\tilde{\Psi} = (I - \tilde{\epsilon}^{-\sigma}\Omega)^{-1}$, and $\tilde{\epsilon}$ is the vector which summarizes $\tilde{\epsilon}_k$ in all the industries. Ψ is the *Influential Matrix* with markups as a supplier. Also, $\tilde{\Delta} = (I - \tilde{\epsilon}^{1-\sigma}\Omega)^{-1}$. And $\tilde{\Delta}$ is the *Influential Matrix* as a consumer.

3.3 Data Description

The data is collected by Standard & Poor Capital IQ (S&P Capital IQ).[4] To investigate the network effect of M&A, we merge three data sets. First is the financial information of the firms. Capital IQ data set covers a majority of the listed firms on the global exchanges. It provides information of 19, 160 incorporated firms in 217 countries, compared to a total number of 43, 572 listed firms worldwide, according to the data from World Bank.[5] This equals to a coverage of 27.5%. Second is the data about M&A transactions. Capital IQ has high quality of transaction data compared to other sources, especially after year 2005.[6] Third is the data about production network. For each firm, Capital IQ provides the identities of its suppliers and customers along the supply chain. With this information, we can easily extract the connections between firms so that to generate a huge adjacency matrix. This is a directed weighted matrix which summarizes all the information related to production network. By doing so, we end up with a panel data from 2007 to 2015 with financial, network and M&A information.

3.4 Effects of M&A on Target firms

3.4.1 Fixed Effect Model

We first use our dataset to look at the effects of M&A through pooled regression model and fixed effect model. The estimating equation have the following form for firm i:

$$log(y_i) = \alpha + \beta_1 MA_i + \beta_2 X_i + FE_{sector} + FE_{country} + \epsilon_i \tag{3.4}$$

$$log(y_{it}) = \alpha + \beta_1 MA_{it} + \beta_2 X_{it} + \beta_3 Z_i + FE_{sector} + FE_{country} + \epsilon_{it}, \tag{3.5}$$

Equation 3.4 is the pooled regression model, while Equation 3.5 refers to the fixed effect (FE) model. y_{it} is the performance measure of firm i in year t. The key right hand side variable is the indicator MA_{it}, which equals 1 for the first year after M&A. X_{it} summarizes time-variant control variables, which includes log level of firm age, log level of firm employment. Z_i summarizes time-invariant control variables. FE_{sector} refers to sector fixed effect, and $FE_{country}$ refers to country fixed effect.

[4] A detailed description of the data set can be seen in Appendix .8. We show our gratitude to Amy Ding Zhao and Junyao Wang, for their initial help with the data set.

[5] The data is displayed here: http://data.worldbank.org/indicator/CM.MKT.LDOM.NO.

[6] The details can be seen in Section .8.

Table 3.1: Effect of Acquisition

	Pooled Regression			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Rev)	Log(Prof)	Log(Prod)	Log(Rev)	Log(Prof)	Log(Prod)
M&A	0.0647*	0.0822*	0.0623	0.104**	0.116**	0.0544
	(2.28)	(2.48)	(1.74)	(3.63)	(3.47)	(1.74)
Observations	50761	49656	50761	50761	49656	50761
Adjusted R^2	0.846	0.791	0.231	0.847	0.791	0.231
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 3.1, the first three columns display the pooled regression results, while the last three columns display the FE result. We choose the log level of three performance measures: revenue, profit and productivity. I extend the Loecker (2013) and Syverson et al. (2015) framework by allowing productivity to evolve endogenously on previous productivities and M&A information. In Appendix .10 we discuss the estimation algorithm in more detail. By allowing productivity to be endogenous, we avoid sample selection and simultaneity issues. In all the six columns, merger and acquisition induce the target firm to perform better. In the FE model, M&A raises annual revenue by 10.47%, profit by 11.6%, significantly. However, the effects of M&A on productivity are not significant in both pooled regression and fixed effect model. This implies that there are no spontaneous effects on productivity. One conjecture is that it takes time for productivity to respond. Productivity improvements are achieved through reallocation control of productive assets into more able managers' hands.[7] The procedure could take more than one year, such as in Syverson et al. (2015), the productivity growth becomes significant after three years in Japanese cotton spinning industry. To test whether this is true in our data sets , we investigate the effects of M&A along with time.

In order to achieve this, we look at the time effect of acquisition by adding two dummies: "Early after M&A dummy" and "Late after M&A dummy". The estimating equations have the following form:

$$log(y_{it}) = \alpha + \beta_1 MA_{it} + \beta_2 MA_{it}^{EA} + \beta_3 MA_{it}^{LA} + \beta_4 X_{it} + \beta_5 Z_i + FE_{sector} + FE_{country} + \epsilon_{it}, \qquad (3.6)$$

[7] Maksimovic and Phillips (2001), Jovanovic and Rousseau (2002), Schoar (2002) are more recent examples of work supporting this view.

where MA^{EA} is an "early post-acquisition indicator". It equals 1 for the second year after the acquisition and 0 otherwise. MA^{LA} is an "late post-acquisition" indicator. It equals 1 for all subsequent post acquisition years after the first two and 0 otherwise. The coefficients on these indicators will reflect how acquired firms' performance measures change after acquisitions.

Table 3.2: Effect of Acquisition: Short Vs Long Term

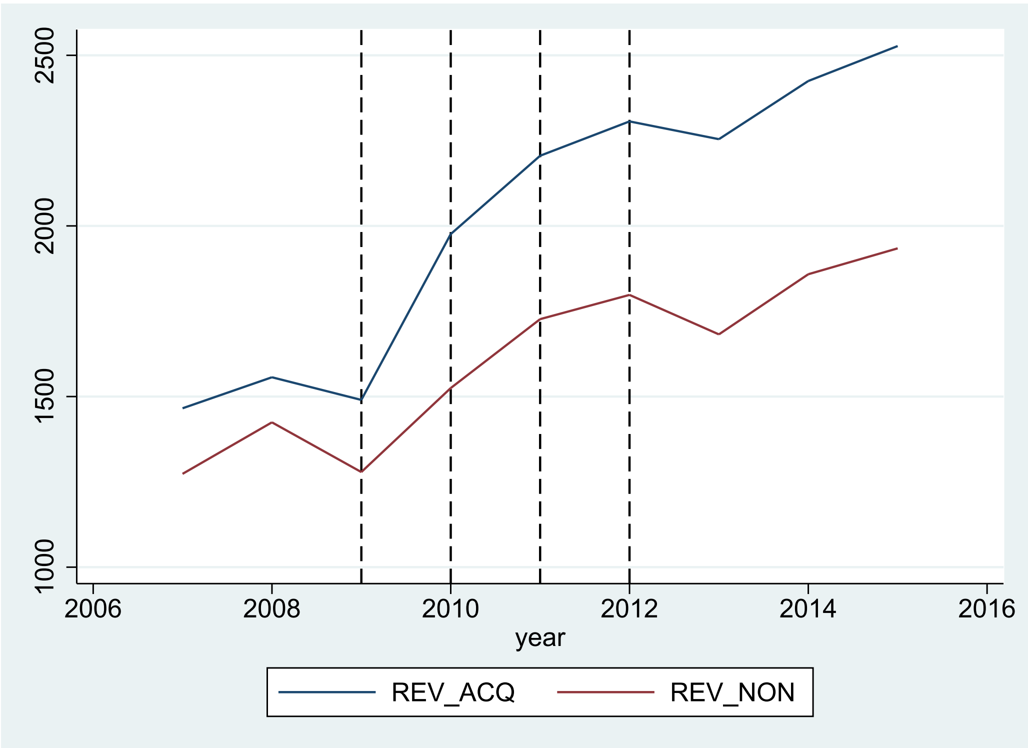
	Panel A: Log Level			Panel B: Growth Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Rev)	Log(Prof)	Log(Prod)	Gr(Rev)	Gr(Prof)	Gr(Prod)
M&A	0.108**	0.102**	0.0339*	0.034**	0.0340**	0.0265
	(3.57)	(3.37)	(2.61)	(3.95)	(6.43)	(1.17)
Early After M&A	0.0941**	0.0921**	0.0470**	0.00663	0.00256	0.0221**
	(2.53)	(3.35)	(3.37)	(0.45)	(0.17)	(3.50)
Late After M&A	0.1070**	0.0925**	0.0573**	0.00236	0.0104	0.0050
	(2.93)	(2.53)	(3.39)	(0.20)	(0.85)	(1.77)
Observations	56853	55526	56853	160101	154791	46877
Adjusted R^2	0.384	0.223	0.240	0.205	0.231	0.214
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel A in Table 3.2 summarize regressions in which dependent variables are in log levels. Merger and acquisition increase revenues and profits immediately after it took place. And the effects are sustainable through time, both in magnitude and significance. The percentage change of revenue is 10.8% directly after M&A, and it becomes 9.41% in early post acquisition years and 10.7% in late post acquisition years. Regarding to profit, the pattern is similar. Profits experience a 10.2% increase in the first year after M&A, then it becomes 9.21% in early post acquisition years, and then to 9.25% afterwards. This gives us a clear picture of substantial effects of M&A on revenues and profits. In contrast, M&A displays increasing effects on productivity with time. The first year after acquisition witnessed a 3.39% increase of productivity. This number climbed to 4.70% in the early post-acquisition years, and then to 5.73% afterwards. Most importantly, the significance is largely improved.

In addition to studying the average level of percentage change, we are also interested in the slope of it. In other words, we are interested in where the large percentage of change come from. Does it come from growing in a constant speed for a long time, or does it come from growing in increasing speed? Panel B in Table 3.2 shows the effect of M&A on growth rate of all the performance measures. Here, the growth rate in period t is defined as the log difference between productivity in period t and $t-1$. The first two columns display the growth rate change of revenues and profits. There are only significant changes in the first year after acquisition. Later on, the differences of growth rates between target firms and their counterparts are not significantly different from zero. This implies that revenues and profits display a hike in the first year after M&A, and then keep increasing in the same speed afterwards, compared to the firms not involved in M&A. However, productivities display a different pattern. Effect on growth rate of productivity is only significant in the early post acquisition years, which can be seen in the last column of Panel B. This means that in the first year after merger and acquisition, productivities of target firms increase with the speed not significantly larger than their counterparts. Then the speed of growing productivities was boosted in the second year after M&A. That is to say, on top of becoming more productive, the target firms improve their productivities faster.



Notes: Data source: Capital IQ

Figure 3.2: The Effects of M&A on Revenues

Notes: Data source: Capital IQ

Figure 3.3: The Effects of M&A on Productivities

3.4.2 Difference In Difference Method

To explain the results above can be difficult if one considers that the identification of counter-factual is vague. Therefore, to accurately estimate the effect of M&A, we launch similar comparisons using the difference-in-difference (DID) method. The treated group includes firms acquired in a specific year, for example, year 2010. While the control group includes firms which were acquired after that year. In our case, it would be year 2011, 2012, 2013 2014 and 2015. By doing this, we avoid the potential endogeneity problem that M&A decision depend on unobserved variables of the acquired firms. The estimating equations have the following form:

$$\begin{aligned} log(y_{it}) = \alpha + \beta_1 TR_i + \beta_2 MA_{it} + \delta_1 TR_i \cdot MA_{it} \\ + \beta_3 MA_{it}^{EA} + \delta_2 TR_i \cdot MA_{it}^{EA} \\ + \beta_4 MA_{it}^{LA} + \delta_3 TR_i \cdot MA_{it}^{LA} + \beta_5 X_{it} + \\ + FE_{country} + FE_{sector} + \epsilon_{it} \end{aligned} \tag{3.7}$$

The variable TR_{ij} is a group dummy indicating whether the firm belongs to the treated group or the control group. Parameters of key interests are $\delta_1, \delta_2, \delta_3$. We display these three coefficients and the coefficient of group indicator TR_i in Table **??**. Out of convenience, we only display the effects in year 2010 below. The results of other years can be seen in Appendix .9. The results are very robust.

Table 3.3: Effect of Acquisition

	Standard Control			Alternative Control		
	(1)	(2)	(3)	(4)	(5)	(6)
	lrev(t)	lprof(t)	lprod(t)	lrev(t)	lprof(t)	lprod(t)
MA(t-1)	0.013*	0.012*	0.007	0.014*	0.011	0.006
	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
MA(t-2)	0.062***	0.069***	0.013*	0.043***	0.041***	0.014*
	(0.025)	(0.032)	(0.007)	(0.016)	(0.013)	(0.007)
MA(t-3)	0.067**	0.068*	0.025*	0.041*	0.045**	0.022**
	(0.033)	(0.028)	(0.013)	(0.016)	(0.022)	(0.010)
MA(t-4)	0.027	0.022	0.021	0.031	0.027	0.020
	(0.019)	(0.017)	(0.020)	(0.021)	(0.020)	(0.017)
MA(t-5)	0.013	0.012	0.007	0.014	0.010	0.011
	(0.019)	(0.018)	(0.017)	(0.019)	(0.020)	(0.018)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	541,370	541,370	541,370	541,370	541,370	541,370
Adjusted R^2	0.175	0.189	0.174	0.187	0.219	0.203

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Summary Statistics I

Variable	**Treated Group**	**Control Group**
Age	18.1	18.5
Latest Revenue	1325.7	1275.8
Latest Profit	432.9	452.3
Size	219	207
Latest Total Enterprise Value	525.1	519.2

Compared to the results with FE model in Table 3.2, we would like to highlight two important observations. First, the effects of M&A on productivity is more than twice of the effects in FE model. In Table 3.2, the post M&A effects are 3.39%, 4.70% and 5.73% for one year, early and late post M&A, respectively. While the DID results in Table **??** display much larger effects on productivities. The post M&A effects are 12.9%, 12.5% and 11.4% for one year, early and late post M&A, respectively. This implies that comparison with the control group indeed improves our estimation. Second, there is an increase in significance. In Table 3.2, the early post acquisition is significant with 95% confidential level; while in Table **??**, the early post acquisition is significant with 99% confidential level. And the late post acquisition effect becomes significant. In contrast to these, there are no changes in effects on revenues and profits. This implies that M&A decisions correlate with productivities of the acquired firms, not revenues or profits. In our case, this means that when buyer firms choose their targets, the decisions hinge on productivities of the target firms, in stead of profitability. This result echoes Syverson et al. (2015).

3.4.3 Instrument Variable: Merger Arbitrage Spread

As an alternative identification strategy, we use an instrument variable "merger arbitrage spread" to estimate the unbiased effects of M&A on performance measures. The idea is that mergers trade at a discount because there is always an uncertainty that a deal will break. The merger arbitrage spread captures this risk of M&A. Therefore, it is correlated with merger and acquisition transaction while do not influence productivities. To validate these two conditions, I firstly introduce the time line of an M&A transaction with Figure **??**.

The first step is invariably private, where a buyer firm approaches a target firm and introduces the idea of an M&A. This usually takes place at the Board of Directors level. In other words, information has not been revealed to the market. Typically, approaches end up with an offer price p^* which is definitely higher than the unaffected stock price p_0 of the target firm. The largest M&A transaction in 2016 is Royal Dutch Shell PLC acquiring BG Group PLC. Shell bid an offer price of 10.63 per share when the market price of BG Group is 8.29 which is a big spread.

Once the companies have shaken hands and agreed on a deal, it comes to the second stage: press release. In this stage, the full merger agreement is released. This will contain all of the important terms of the deal, including the conditions necessary for the deal to close, the required governmental approvals, the representations and warranties for buyers and sellers. When the information is revealed to the market, usually, the price of acquired firm increases to p_1, which is smaller than P^*. The spread $p^* - p_1$ is the *merger arbitrage spread*. It reflects the market expectation on the risk of M&A failure. The higher this risk is, the bigger merger spread will be.[8] In the following, I will

[8] There are scenarios where $p_1 > p^*$. For instance, On the day of announcement, April 8th 2015, BG Group experienced a hike of stock price: from 8.29 to 11.53, which is bigger than the offer price 10.63. This negative spread implies that market expects a higher offer price to emerge later on.

elaborate why it is a good IV.

Finally, it comes to the last stage when M&A begins.[9] Once the target share holders have approved the deal, it usually closes immediately after. The target firm's stock price will cease trading. While in Europe, where deals are often structured as tender offers, the stock post-tender will still trade. This stock is not eligible for tendering, and it is usually highly illiquid.[10]

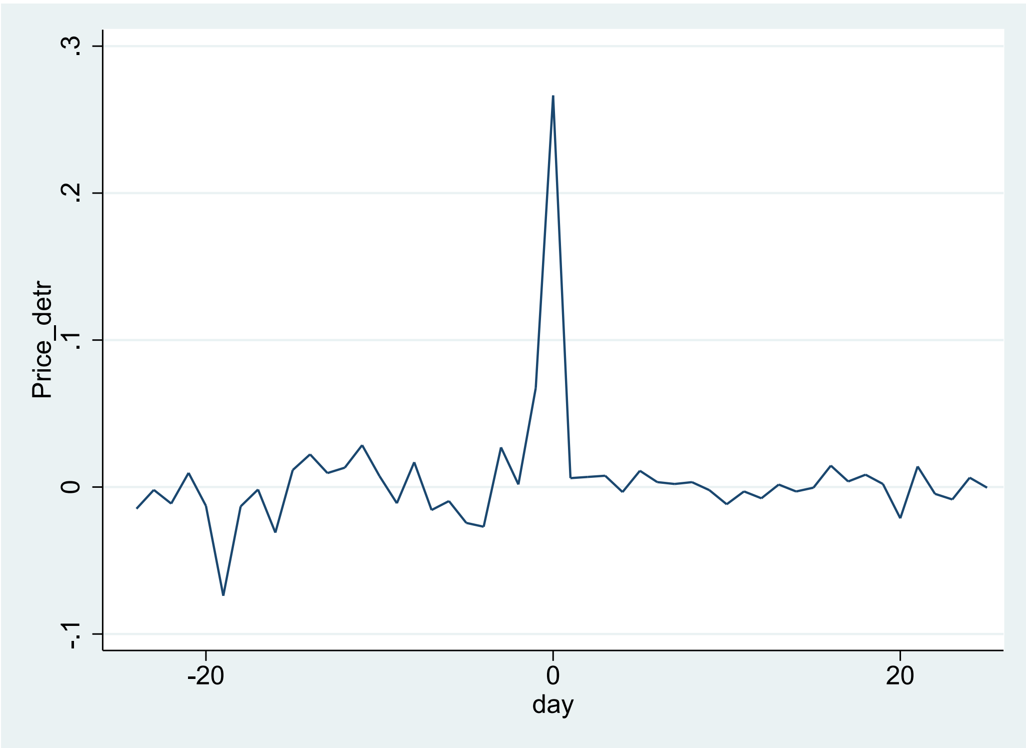


Figure 3.4: Growth Rate of Stock Price

[9]Before the last stage, there will be a lot of procedures to go through. The parties will make the required regulatory filings. The most common filing is Hart Scott Rodino Act of 1976 (HSR). This is a notification to the government that is required for every deal over a certain threshold. The antitrust investigation will take place in this procedure. In some highly regulated industries, such as banking and utilities, there are other necessary regulatory filings. If the buyer firm is a foreign firm, it need to submit a Committee on Foreign Investment in the United States (CFIUS) file.

[10]In Europe, it is typical for a tender offer to be conditioned on 90% acceptance. In this case, the shareholder would tender their stock and not know if the company has accepted the stock or not.

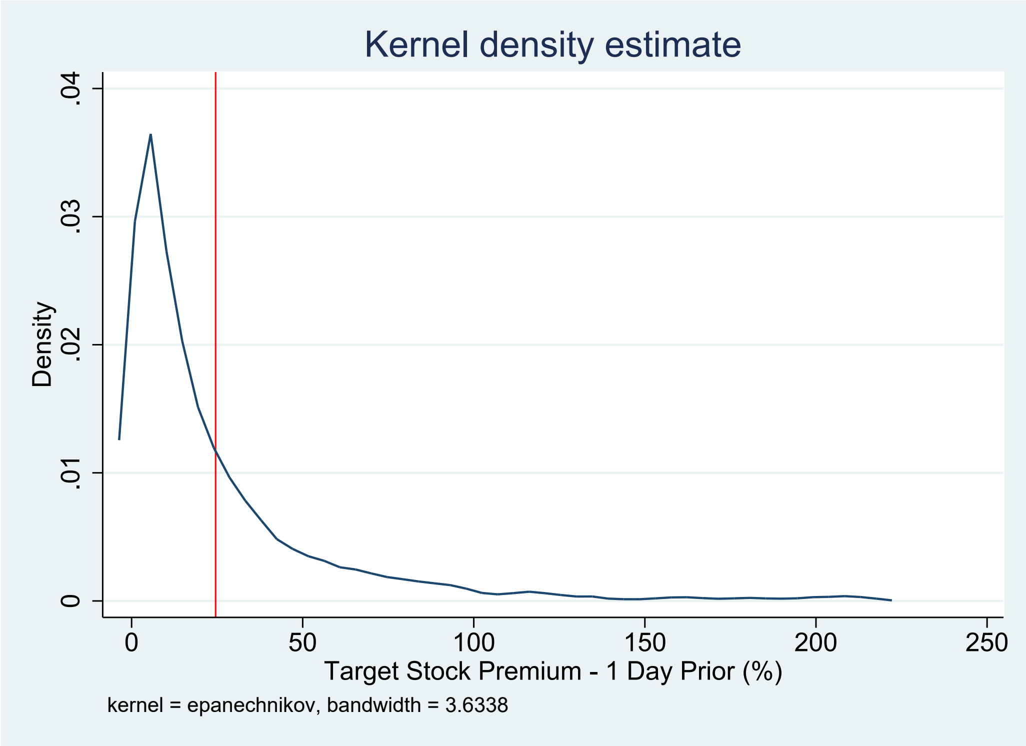


Figure 3.5: Density of Price Difference

3.5 Upstream/Downstream/Rebound Effects of M&A on Firms

3.5.1 Descriptive Evidence

Before any econometric analysis, I display some statistical features about network effects of M&A. The network effect of M&A refers to the indirect effects of M&A on a firm transmitted through production networks. It could be first-order or higher-orders. In this section, we focus on first-order network effects. In the following sections, we extend to higher-order network effects.

First, we display the features of suppliers and prevalence of supplier related M&A. It can be observed from Panel A in Table 3.6 that 85.39% firms have at least one supplier. This implies that the majority of firms are connected in the production network. Among those 85.39%, 75.83% are connected with firms whose corporate information are available in Capital IQ. The rest are connected with firms out of Capital IQ. For these firms, We have no access to their financial information, however, we know their existences. Then let us investigate the prevalence of supplier related M&A. There are 12.76% of firms which have at least one supplier being acquired during time window 2007-2013. If we apply the Law of Large Numbers (LLN), this means that the probability of one

Table 3.5: Effect of M&A

First-Stage Dependent Variable: M&A			
Merger spread	0.022^{***}		
	(0.007)		
F-Statistics	66.64		
Second-Stage Dependent Variable			
	(1)	(2)	(3)
	lrev(t)	lprof(t)	lprod(t)
MA(t-1)	0.012	0.011	0.006
	(0.008)	(0.007)	(0.006)
MA(t-2)	0.042^{***}	0.043^{***}	0.013^{*}
	(0.011)	(0.012)	(0.007)
MA(t-3)	0.039^{**}	0.041^{*}	0.020^{*}
	(0.018)	(0.020)	(0.010)
MA(t-4)	0.023	0.024	0.021
	(0.017)	(0.016)	(0.019)
MA(t-5)	0.015	0.013	0.008
	(0.018)	(0.017)	(0.016)
Firm FE	YES	Yes	Yes
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	541,370	541,370	541,370
R^2	0.215	0.209	0.213

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

firm having "Non-Zero Acquired Suppliers" is 12.76%. Together with average supplier number of 2.77 in Panel B, this refers to the probability of getting acquired being 14.57%, which echoes the probability of 15.17% in Figure 38. The last row in Panel A displays that it is almost impossible that a firm has an acquired supplier every year.

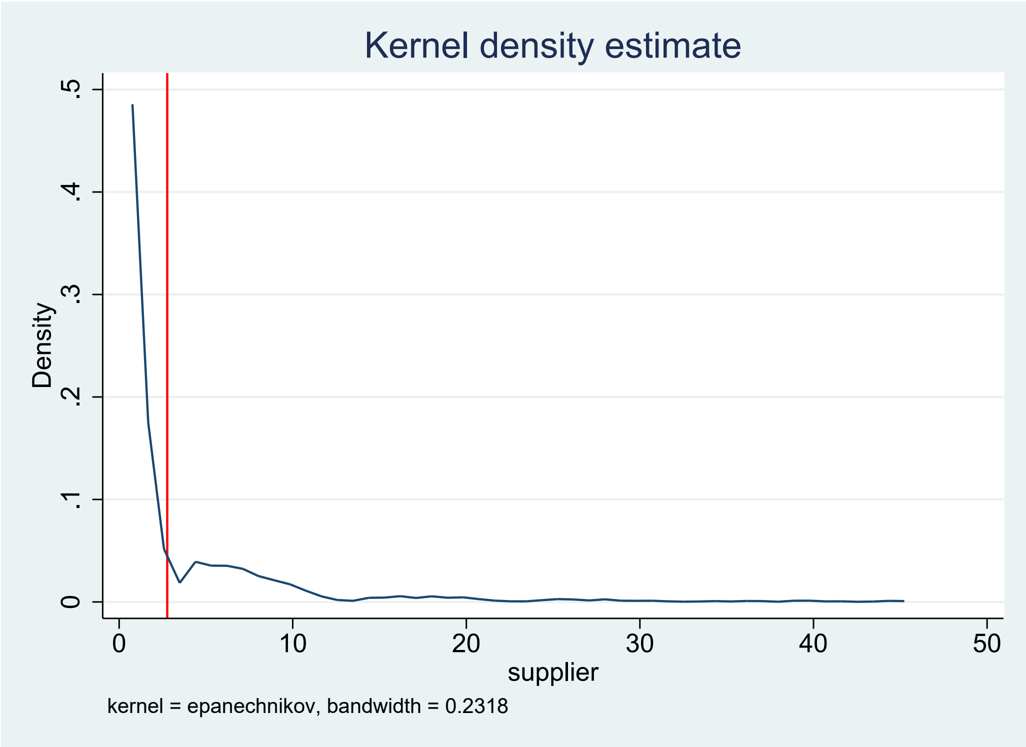
Panel B describes the fundamental summary statistics of three important variables: total suppliers, and acquired suppliers in two different samples. The first row tells us that a representative firm in our sample has 2.77 suppliers, which points to an average degree of 2.77. The range of suppliers falls between 0 and 46. Figure 3.6 display the distribution of suppliers. It can be inferred from moments of the distribution that this density function is very close to a Type I-Pareto Distribution with $\alpha = 1.8$. That is to say, this network has granularity.[11] The second and third row both display the variable of acquired suppliers, however in different samples. The second row picks up firm in the year when supplier-related M&As happen. The third row picks up firms not only in the year M&As happen, but also all the other years during the time window. Therefore, the third row should yield a smaller number. In the year when M&As happen, firms have 1.63 suppliers acquired. While for firms ever involved in supplier-related M&As, they have 0.51 suppliers acquired. That is to say, they have 1 supplier acquired every two years.

Table 3.6: Summary Statistics

Panel A					
Variable	**Fraction**	**Sample Size**			
Non-zero Suppliers	85.39%	117,159			
Non-zero Acquired Suppliers	12.76%	117,159			
Non-zero Acquired Suppliers	0	117,159			
Panel B					
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Sample Size**
Total Suppliers	2.77	15.83	0	46	117,159
Acquired Suppliers	1.63	1.93	1	42	4,635
Acquired Suppliers	0.51	1.32	0	42	14,952

[12] [13] [14] [15]

[11] InXXX, they have some distribution in a granular network......
[12] The samples are firms who have at least one acquired suppliers during time window 2007-2013.
[13] The samples are firms who have non-zero acquired suppliers in each of the year from 2007 to 2013.
[14] The samples are firms who have non-zero acquired suppliers in each year.
[15] The samples are firms who have non-zero acquired suppliers in all the seven years, from 2007 to 2013.



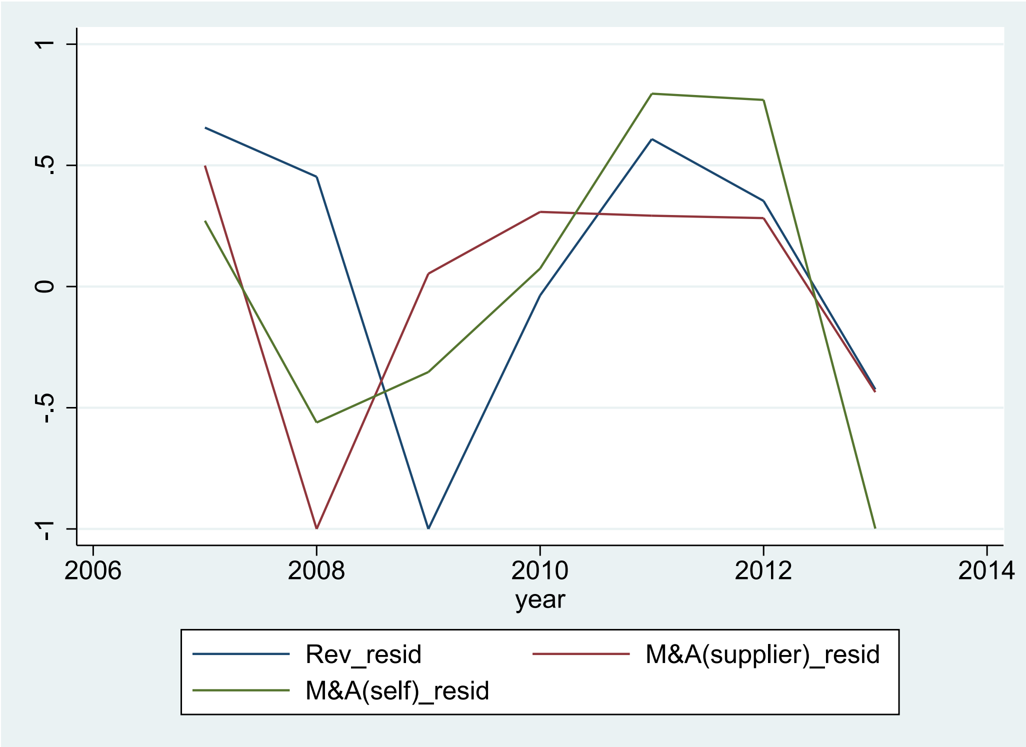
Notes: Data source: Capital IQ

Figure 3.6: Probability Density Function of Suppliers

Then, before running regressions, I study statistically whether supplier-M&As have an influence on firms' revenues.

Figure 3.8 displays the business cycle of self-M&As, supplier-M&As and revenues, based on our data set. We detrend all variables using a linear growth model.[12] After that, we project the residuals into space [-1,1], since we are only interested in shapes of the curves instead of their levels. We notice two important features. First, self-M&As and supplier-M&As have very similar pattern. They both experienced a drop in 2008 when the global financial crisis broke out. Then they increased smoothly until they reached a plateau around 2010-2012. After that, they both dropped in 2013. Second, revenues follow the cycle of M&A events, with one-year lag. Revenues had a deep in 2009 and increased afterwards. This indicates that M&As and revenues are correlated. This, without any doubt, is not an argument for causality. But it provides us with a necessary condition to investigate causality .

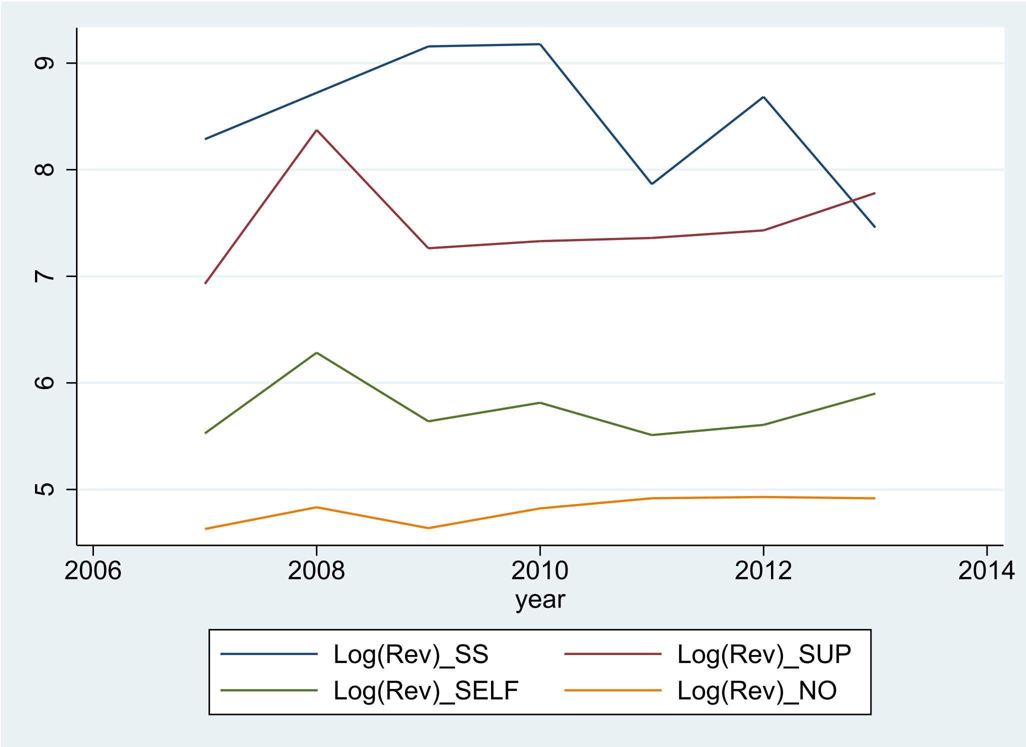
[12]Figure 3.8 displays the residual from running a regression $R_{i,t} = \alpha + \beta \cdot t + \epsilon_{i,t}$, where $R_{i,t}$ stands for revenue of firm i in year t.



Notes: Data source: Capital IQ

Figure 3.7: Self-M&A, Supplier-M&A and Revenues

Next, we would like to explore more about M&As' effects on revenues, statistically. This can be done in many different ways. In this section, we use two methods. With the first method, we compare revenues of firms which are involved in different types of M&As. With the second method, we compare firms' revenues before and after their M&A events. Figure 3.8 displays the revenues for four groups of firms: the firms which are engaged in both self-M&A and supplier-M&As, the firms which are engaged in self M&As, the firms which are engaged in supplier-M&A and firms without any M&As. It is obvious that firms with both M&As have the largest revenues, followed by firms with only supplier-M&A, then firms with only self-M&As. And the last are firms with no M&As. Therefore, we can roughly draw the conclusion that supplier-M&As and self-M&As both have positive effect on firms' revenues. (We are confident about the effects of self-M&A according to the analysis in Section 3.4.) And supplier-M&As have larger effect than self-M&As. That is to say, network effects of M&A are larger than direct effects of M&A.

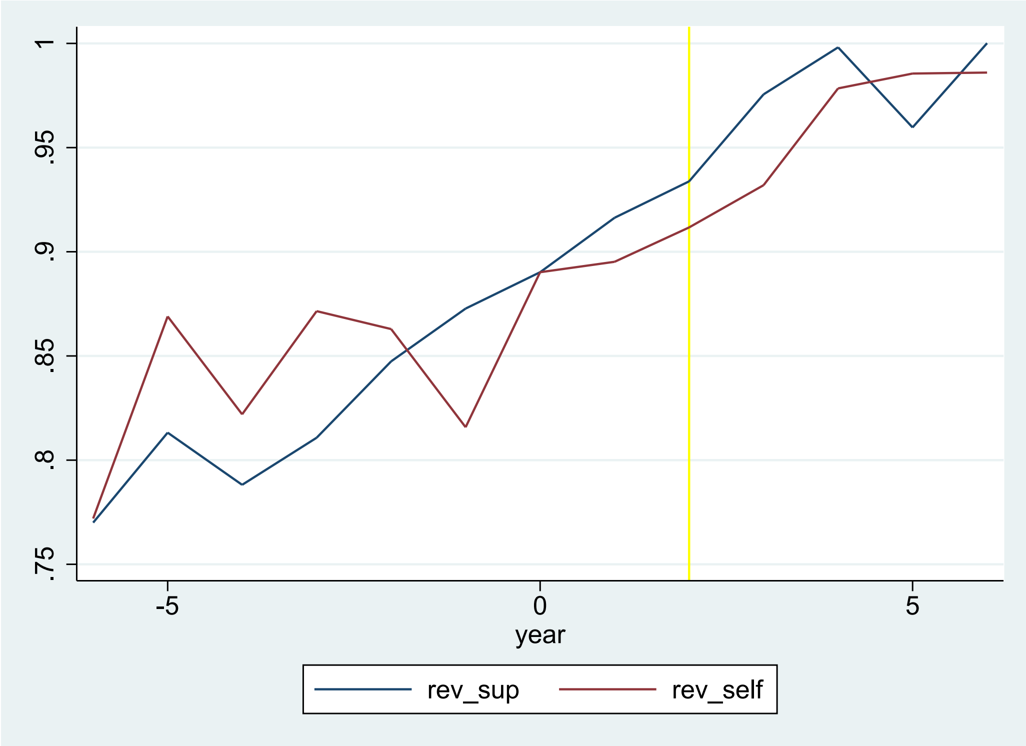


Notes: Data source: Capital IQ

Figure 3.8: Revenues by Groups: Self-Supplier-M&A, Self-M&A, Supplier-M&A and Non-M&A

Figure 3.9 displays revenues before and after supplier-M&As take place. The horizontal axis range from [-7,7],[13] and t=0 is the year when M&As happen. Revenues are projected to the space of [-1,1]. We also normalize the revenues of supplier-M&A by its self M&A counterpart in year 0. We can observe from the graph that revenues keep increasing after each type of M&As. Also, firms hit by supplier-M&As have higher revenues than firms hit by self-M&As. This further supports our hypothesis that supplier M&As might have nontrivial positive effects on revenues. And this effect might be higher than that of self-M&As.

[13] There are 14 years because firms have M&A in different years. For firms having M&A in 2007, their t ranges from 0 to 7; while for firms having M&A in 2013, their t ranges from -7 to 0.



Notes: Data source: Capital IQ

Figure 3.9: Revenues Across Years

To sum up, a majority of firms are connected in the production network. This network is very likely to have granularity. A distinctive fraction of firms are involved in supplier M&A events, at least once during the time window. Occurrences of self-M&A and supplier-M&A are both correlated with firms' increased revenues. And the firms with supplier-M&As generate higher revenues than those with self-M&As.

3.5.2 Results

The mechanism is very straightforward. I will illustrate it with Figure **??**. Firm A has three upstream firms B1, B2 and B3.[14] They sell intermediate goods to A. Suppose that in year t, B1 is acquired by firm C. According to the analysis in Section 3.4, B1 will have larger revenues after year t, and higher productivities after year t+1. Either could lead to an increase of intermediate goods that it sells to A. Automatically, it leads to an increase of revenues for firm A. And this shock will propagate through input-output network to other downstream customers, so on and so forth.

What we want to test in this section is whether M&As on supplier firms will lead to an increase

[14]We choose three suppliers because the average degree is 2.77, according to Table 3.6.

of revenues for their customers. After that, we investigate the mechanism through which this takes place.

Regressions. In this section, we use FE model, DID model and IV method to estimate this effect. The FE estimating equation takes the following form:

$$\begin{aligned} log(y_{it}) = \alpha + \beta_1 \cdot MA_{it}^{self} + \beta_2 \cdot MA_{it}^{sup} + \beta_3 \cdot N_{sup^{TOT}} + \beta_4 \cdot N_{sup^{MA}} \\ + \beta_5 \cdot X_{it} + \beta_7 \cdot Z_i + FE_{sect} + FE_{country} + \epsilon_{it}, \end{aligned} \tag{3.8}$$

MA_{it}^{self} in an indicator of whether firm i is acquired in year t. MA_{it}^{sup} is an indicator of whether firm i's suppliers are acquired. $N_{sup^{TOT}}$ is number of total suppliers of firm i. $N_{sup^{MA}}$ is number of acquired suppliers. X_{it} is a set of time-variant control variables, while Z_i is a set of time-invariant variables. FE_{sect} is sector fixed effect and $FE_{country}$ is country fixed effect.

Table 3.7: Downstream Effects of M&A (IV)

	R&D Group			No R&D Group		
	(1)	(2)	(3)	(4)	(5)	(6)
	lrev(t)	lprof(t)	lprod(t)	lrev(t)	lprof(t)	lprod(t)
SupMA(t-3)	0.027***	0.026***	0.014	0.012	0.014	0.008
	(0.009)	(0.011)	(0.008)	(0.007)	(0.008)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes			
Observations	218,167	218,167	218,167	323,203	323,203	323,203
Adjusted R^2	0.214	0.218	0.210	0.209	0.223	0.211

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 Effects of Changing Network Structure

In this section, we investigate how M&A changes the network structure, and how this change contributes to propagation of idiosyncratic shock. According to Acemoglu et al. (2012) and Oberfield (2017), shocks get propagated because the asymmetric structure of network. In other words, there exists some firms who have "granular" influence on others. They play the role of hubs. Shocks move towards these hub firms and then branch out to rest of the economy.

Table 3.8: Downstream Effects of M&A (IV)

	(1) lrev(t)	(2) lprof(t)	(3) lprod(t)
SupMA(t-1)	0.003	0.010*	0.003
	(0.005)	(0.009)	(0.008)
SupMA(t-2)	0.022*	0.023	0.010
	(0.011)	(0.014)	(0.007)
SupMA(t-3)	0.017*	0.028*	0.025*
	(0.098)	(0.014)	(0.013)
SupMA(t-4)	0.013	0.020	0.011
	(0.019)	(0.017)	(0.017)
SupMA(t-5)	0.011	0.020	0.011
	(0.019)	(0.015)	(0.014)
Firm FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	541,370	541,370	541,370
Adjusted R^2	0.201	0.197	0.217

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Rebound Effects of M&A (IV)

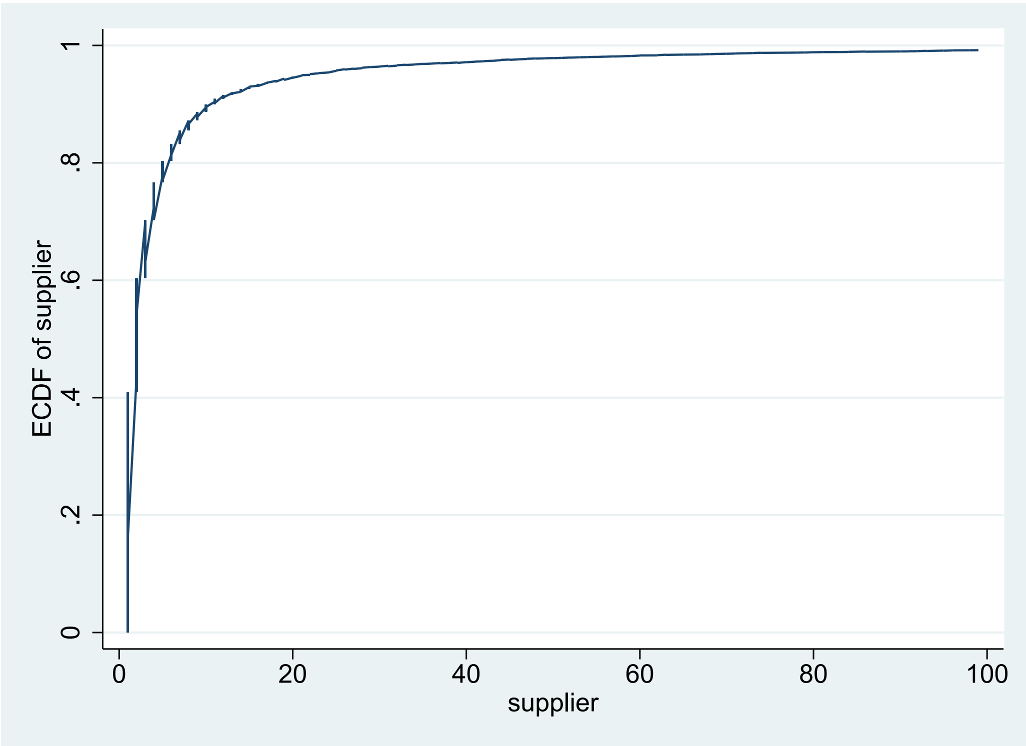
	R&D Group			No R&D Group		
	(1) lrev(t)	(2) lprof(t)	(3) lprod(t)	(4) lrev(t)	(5) lprof(t)	(6) lprod(t)
PeerSupMA(t-5)	-0.016**	-0.012*	0.003	0.006	0.004	0.007
	(0.009)	(0.006)	(0.008)	(0.007)	(0.004)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes			
Observations	201,723	201,723	201,723	339,647	339,647	339,647
Adjusted R^2	0.185	0.198	0.180	0.210	0.221	0.207

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6.1 Hub Firms and Periphery Firms

To investigate the propagation, first and foremost, we define hub firms in our sample. According to theory, hub firms should be those sitting on the fat tail of distribution. Figure 3.10 displays the cumulative density function (CDF), and Figure 3.6 displays the probability distribution function (PDF) of suppliers. We observe that the distribution of suppliers has large skewness and is close to the power law distribution. Table 3.10 shows that more than 80% of the suppliers are owned by 30% of the firms. And more than half of the suppliers are owned by 5% of the firms. So we define one firm as a "hub firm" if it has more than 22 suppliers.[15] This leaves us with 5852 hub firms in the sample.



Notes: Data source: Capital IQ

Figure 3.10: Revenues by Groups: Self-Supplier-M&A, Self-M&A, Supplier-M&A and Non-M&A

Then, we describe hub firms in this economy. Are they large firms? Are they profitable firms? Are they more volatile? In the following analysis, all firms fall into two groups: the hub firm and the periphery firm. Table 3.11 displays the average number of suppliers, revenue, profit, size, age and volatility of these two groups.[16] We observe that hub firms are larger and more profitable than

[15] Robustness check can be done with respect to different definitions.

[16] The volatility is defined as the standard deviation of sales' growth rate, following Gabaix (2011) and Kranarz et al. (2016).

Table 3.10: Distribution of Suppliers

Firms	**Percentiles**	**Share of Suppliers**
Top 1%	57	28.64%
Top 5%	22	53.85%
Top 10%	11	64.10%
Top 20%	5	76.76%
Top 30%	3	83.42%

periphery firms. They hire more workers, generate higher enterprise value and have longer history. However, they are much less volatile than the periphery firms. This is not counter-intuitive when we consider the fact that larger firms are much less volatile than small firms, proved by a lot of empirical research (XXXXX).

Table 3.11: Hub Firms and Periphery Firms

Variables	**Hub Firms**	**Periphery Firms**
Number of Suppliers	69.20	3.20
Revenue (EURmm)	26183.74	1969.24
Profit (EURmm)	8125.69	564.37
Total Enterprise Value (EURmm)	39088.55	3409.69
Size	62919	5482
Age	80.10	52.40
Volatility	0.49	11.33

Next, we explore how M&A change numbers of hub firms and structures of input-output network.

There are some questions: 1. cross-industry mergers should be more important than intra-industry mergers. 2. Hub firms should be those with numerous connections. More connections leads to more influential on one hand. On the other hand, more connections diversify shocks. How do these two effects work against each other?

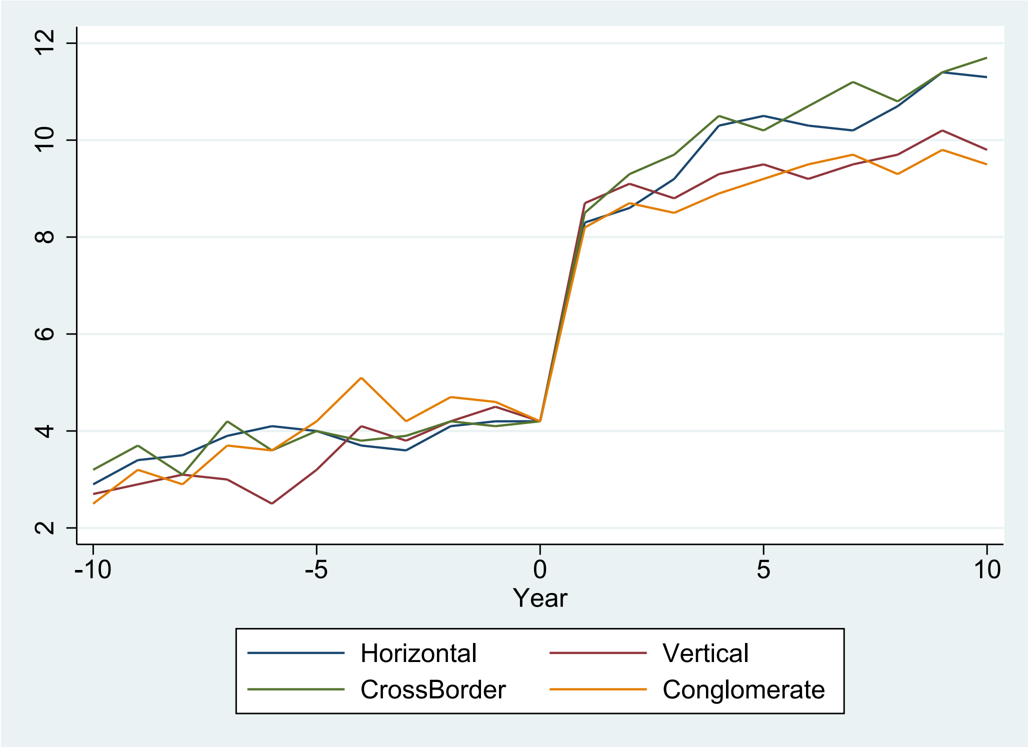
3.6.2 Firm-level Evidence

In this section, we are interested in two questions. First, how merger and acquisition changes network structure. Second, how changes of network structure affect propagation. To investigate the first question, we document how the number of customers change before and after M&A.

Figure 3.11 displays the number of customers pre-M&A and post M&A, for the combined firms which are buyer firm and target firm. Zero on the time-axis represents the year of M&A. We group M&As into four categories: horizontal M&As, vertical integrations, cross-border M&As, and conglomerate M&As. We observe that right after M&A, the number of customers almost double its size, for the combined firms. And it is true for all the M&A transactions. And the number of customers keep increasing in the second year. And the speed is larger than ex ante. This implies that M&As increase the out-degree of firms by merging them.

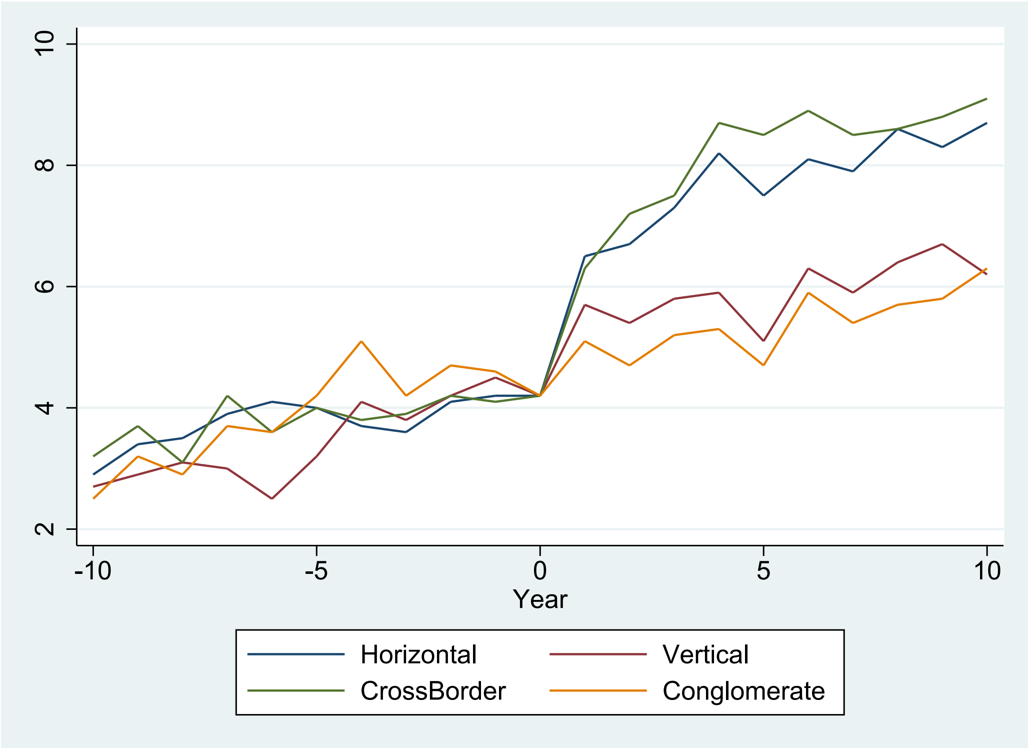
However, this does not display the real change of customers for the target firm. Because target firms do not necessarily sell to every customer of its buyer firm. Figure 3.12 displays the change of customers with whom the target firm actually trade. We observe that there is still a large increase in the number of customers after M&A. The difference to Figure 3.11 is around 3 customers. This implies that M&A increase out-degrees of firms not only by merging them but also introducing new customers to the target firms. Also, we find that cross-border M&A and horizontal M&A bring much more customer to the target firms than vertical M&A and conglomerate M&A. Conglomerate M&A brings almost zero customer to the target firms. In other words, conglomerate M&A does not change the network structure, and the target firm run as an independent firm.

Then, we would like to understand the sources of these new customers. Table 3.12 displays the fractions of three sources: new customers who have direct link with the buyer firms, new customer who have indirect link with the buyer firms, and new customers who are not linked with the buyer firms. We define the link as indirect if the two firms reach each other within 3 direct links. Otherwise, we define the link as weak. We observe that for horizontal M&A and cross-border M&A, most new customers are directly or indirectly linked with the buyer firm. In other words, M&A increase out-degree of firms not only by merging them, but also by developing new customers for them.



Notes: Data source: Capital IQ

Figure 3.11: Number of Customers



Notes: Data source: Capital IQ

Figure 3.12: Number of Customers

Table 3.12: Number of New Customers

	Direct Link	**Indirect Link**	**Weak Link**
Horizontal	2.17	1.38	0.78
Vertical	0.78	0.93	1.34
Cross-Border	2.65	2.31	0.91
Conglomerate	0.59	0.21	1.78

Table 3.13, 3.14, 3.15 and 3.16 display the features of direct, indirect and weak customers for each type of the M&A transactions.

Table 3.13: Features of New Customers: Vertical Integration

Types	Number	Degree	Distance	Size	Age	Revenues
Direct	0.78	5.17	1	1,732	32.14	3458.15
Indirect	0.93	5.62	2.31	1,825	27.81	4109.32
Weak	1.34	4.48	7.86	538	28.39	3890.70

Table 3.14: Features of New Customers: Horizontal M&A

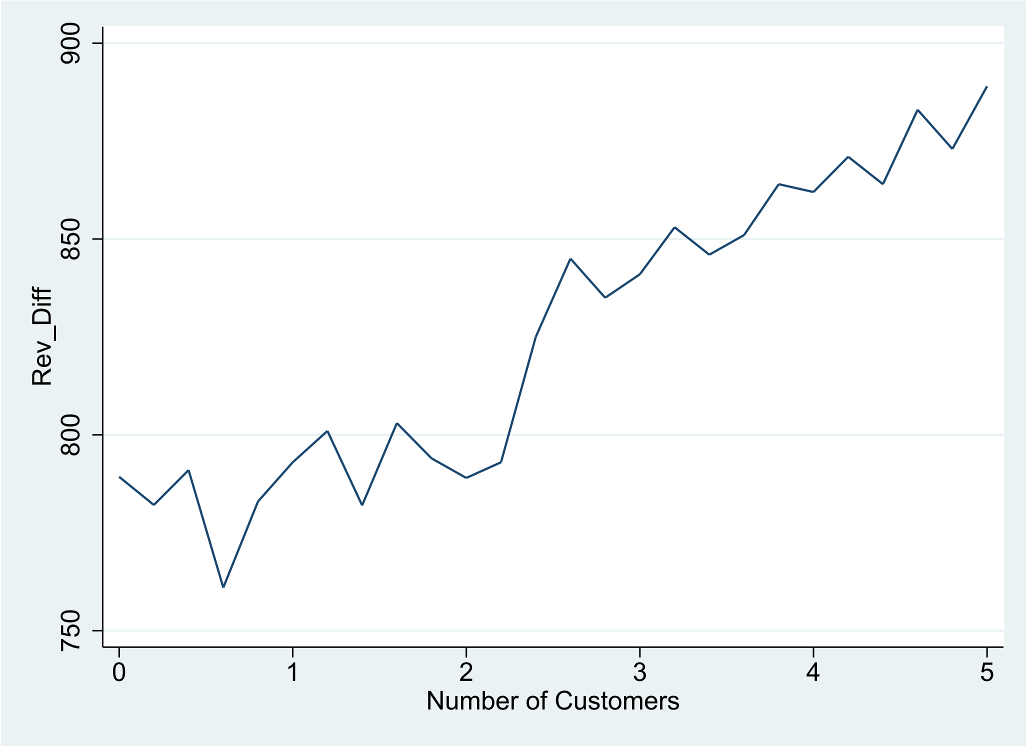
Types	Number	Degree	Distance	Size	Age	Revenues
Direct	2.17	14.17	1	1,638	35.46	3598.23
Indirect	1.38	2.62	1.97	1,603	31.26	4290.73
Weak	0.78	3.48	6.92	792	29.41	3920.12

Table 3.15: Features of New Customers: Cross Border M&A

Types	Number	Degree	Distance	Size	Age	Revenues
Direct	2.65	13.17	1	1,412	33.41	3672.01
Indirect	2.31	4.62	1.37	1,510	32.70	4012.56
Weak	0.91	1.48	8.57	937	28.36	3812.37

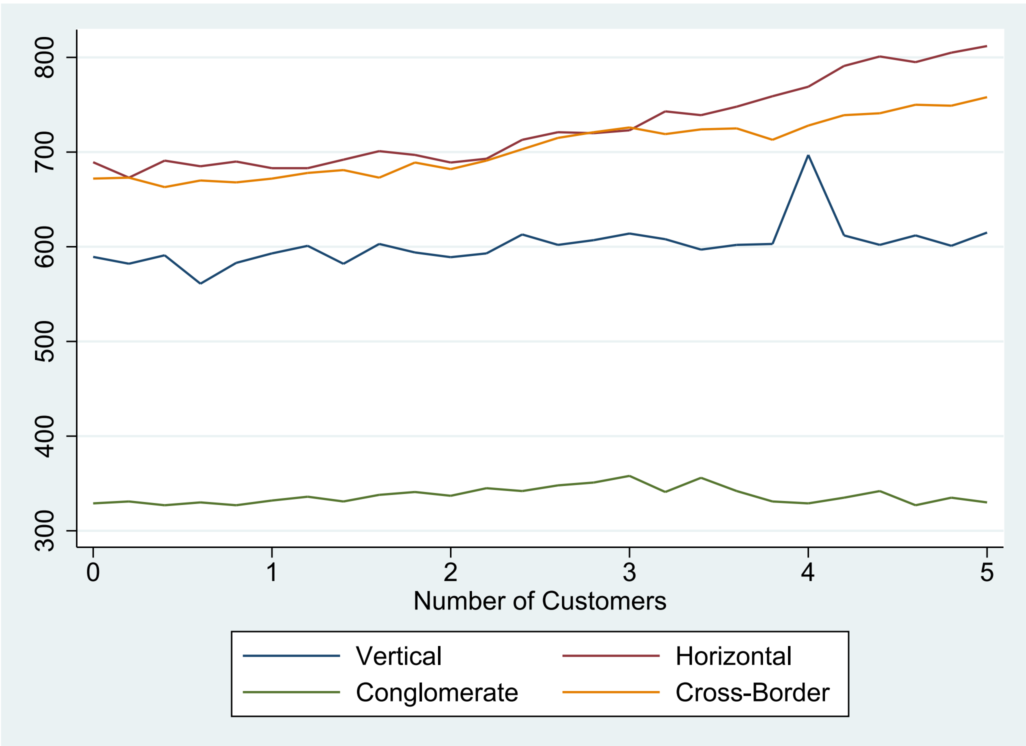
Table 3.16: Features of New Customers: Conglomerate M&A

Types	Number	Degree	Distance	Size	Age	Revenues
Direct	0.59	2.31	1	1,708	32.71	3983.01
Indirect	0.21	1.43	1.52	1,631	35.80	3945.92
Weak	1.78	1.51	7.12	912	30.16	3712.57



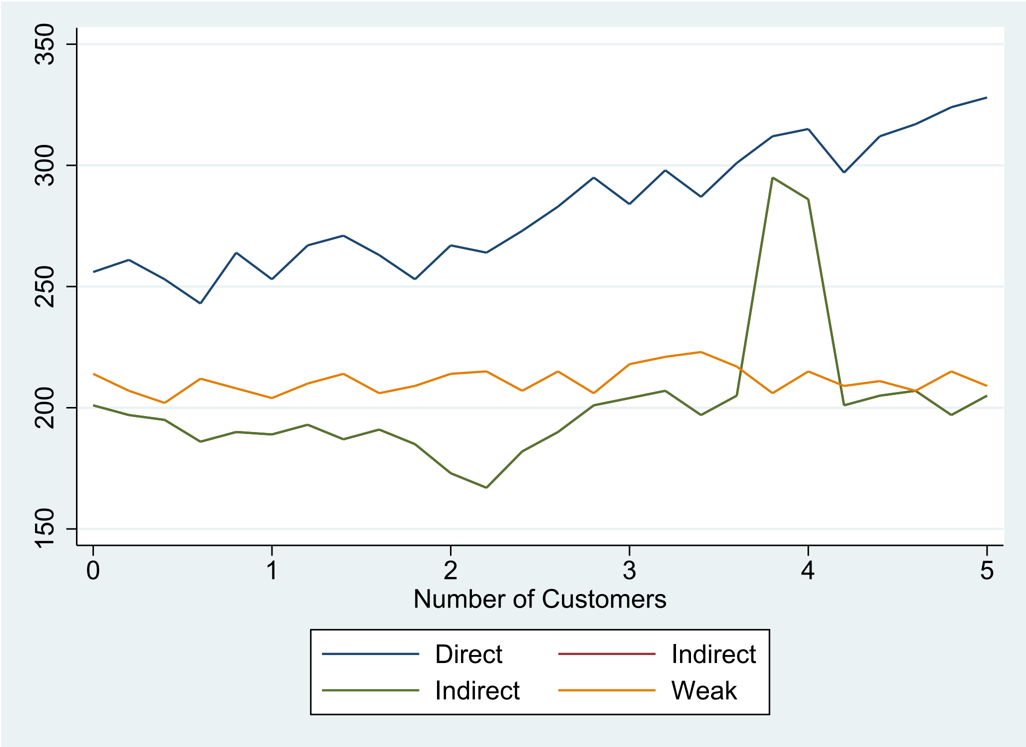
Notes: Data source: Capital IQ

Figure 3.13: Revenue Differences of Target Firms



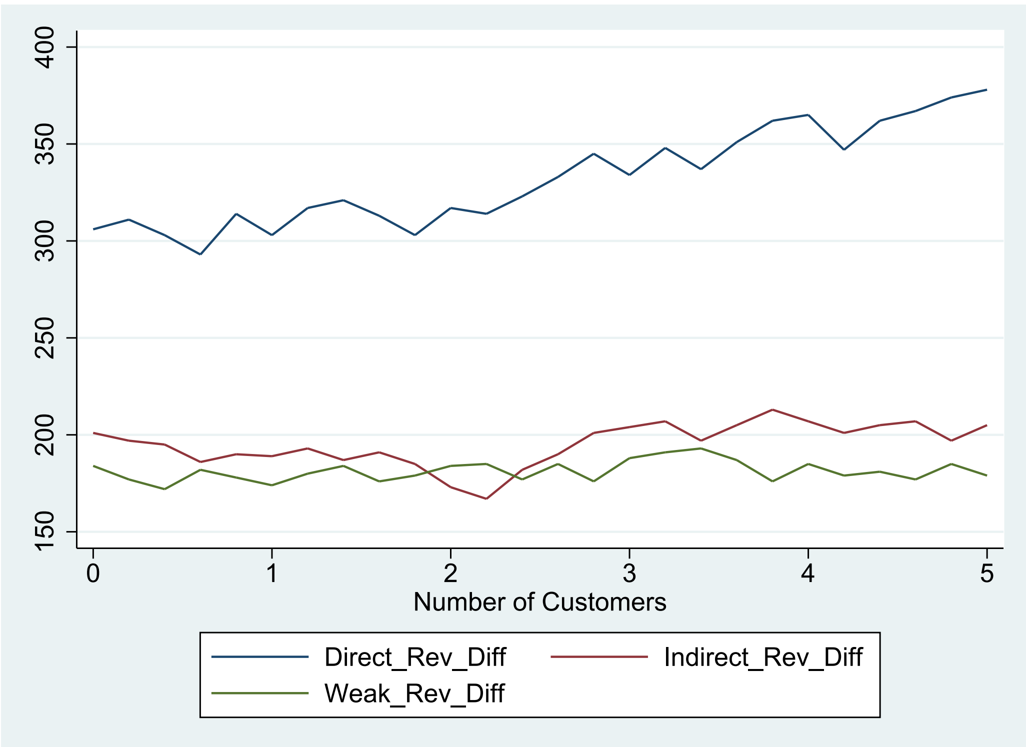
Notes: Data source: Capital IQ

Figure 3.14: Revenue Differences of Target Firms



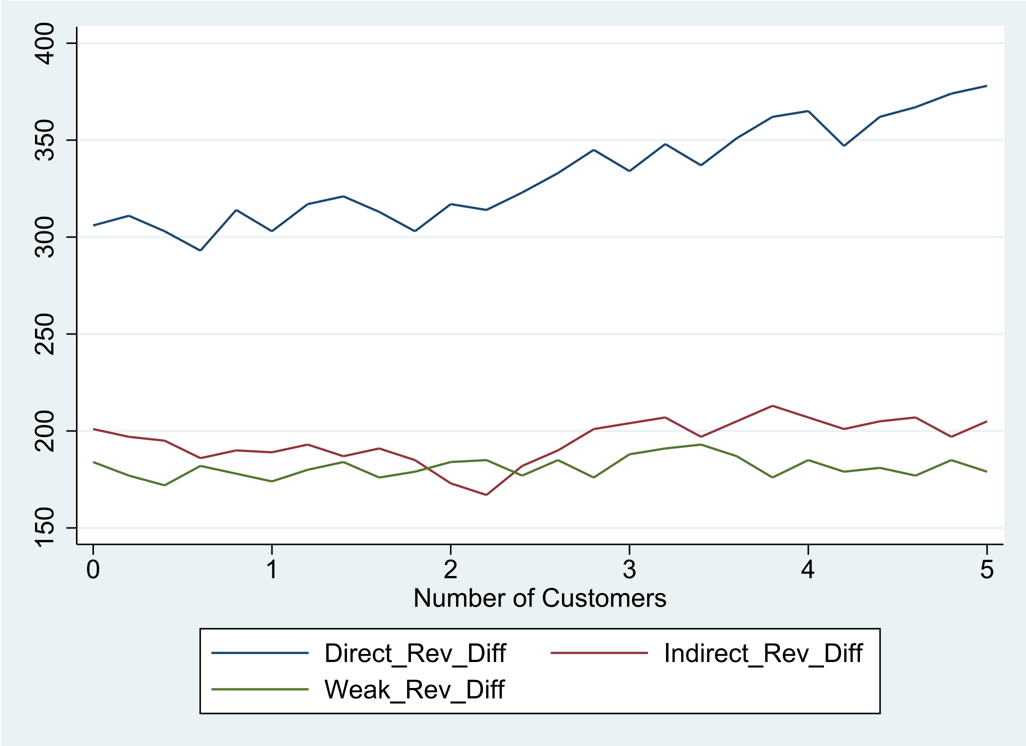
Notes: Data source: Capital IQ

Figure 3.15: Revenue Differences of Target Firms



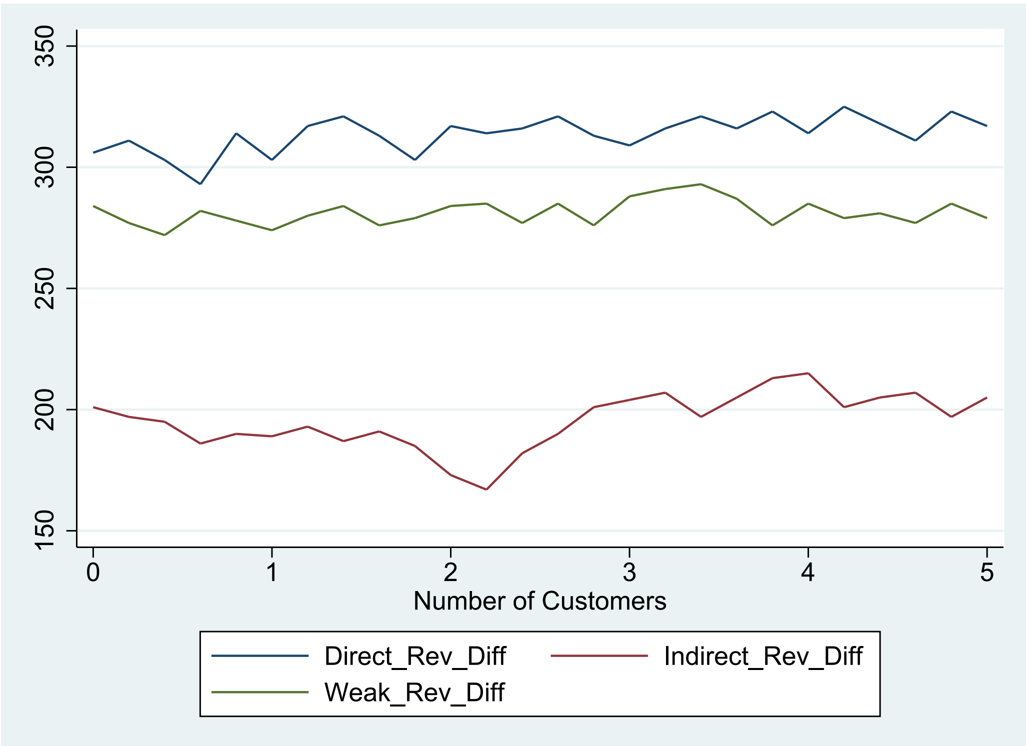
Notes: Data source: Capital IQ

Figure 3.16: Revenue Differences of Target Firms



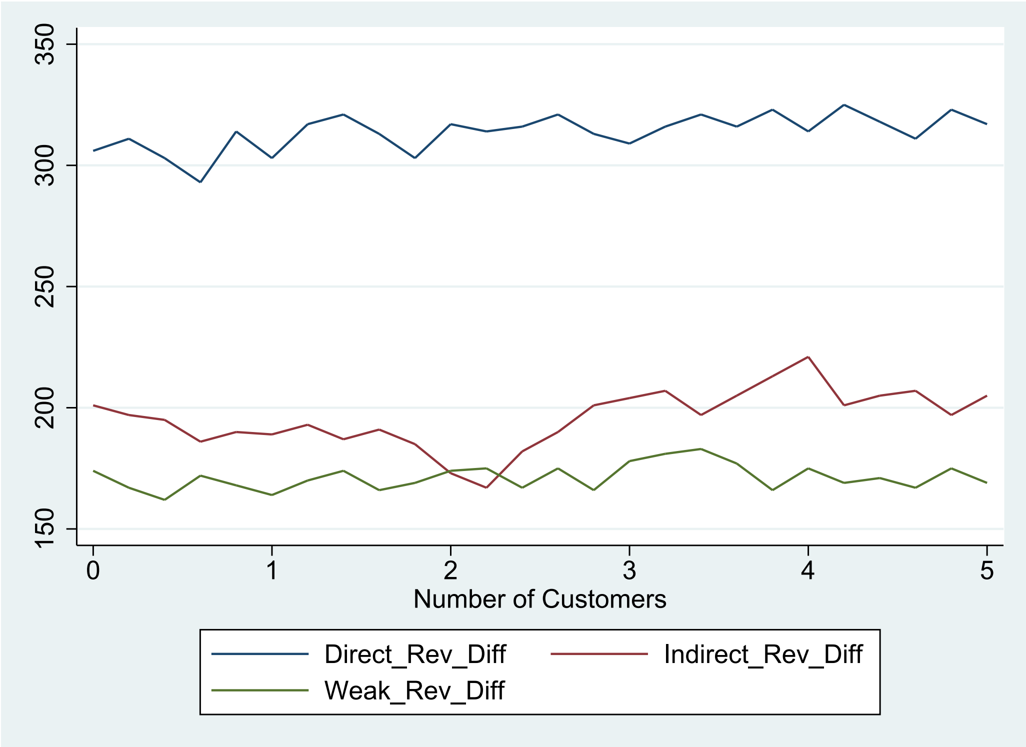
Notes: Data source: Capital IQ

Figure 3.17: Revenue Differences of Target Firms



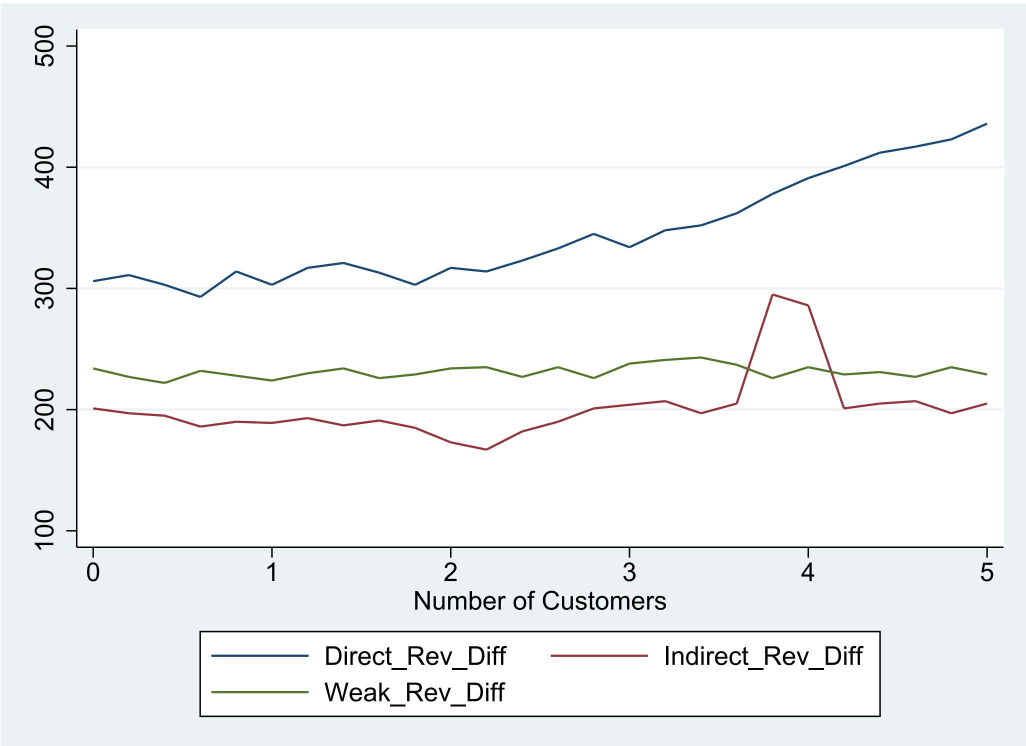
Notes: Data source: Capital IQ

Figure 3.18: Revenue Differences of Target Firms



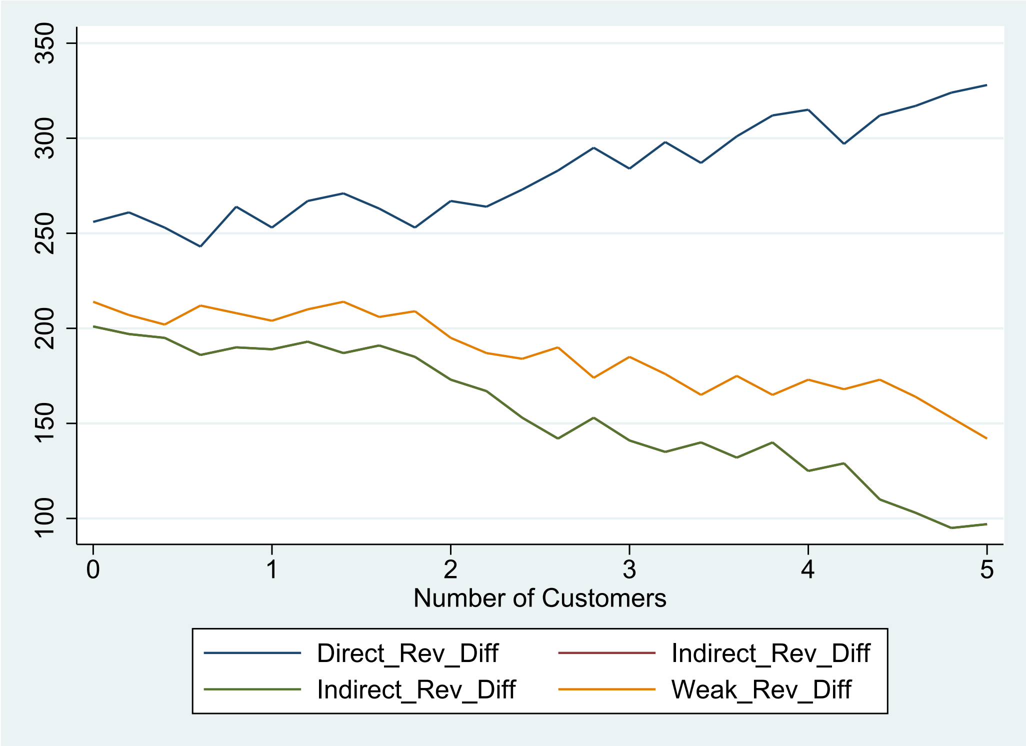
Notes: Data source: Capital IQ

Figure 3.19: Revenue Differences of Target Firms



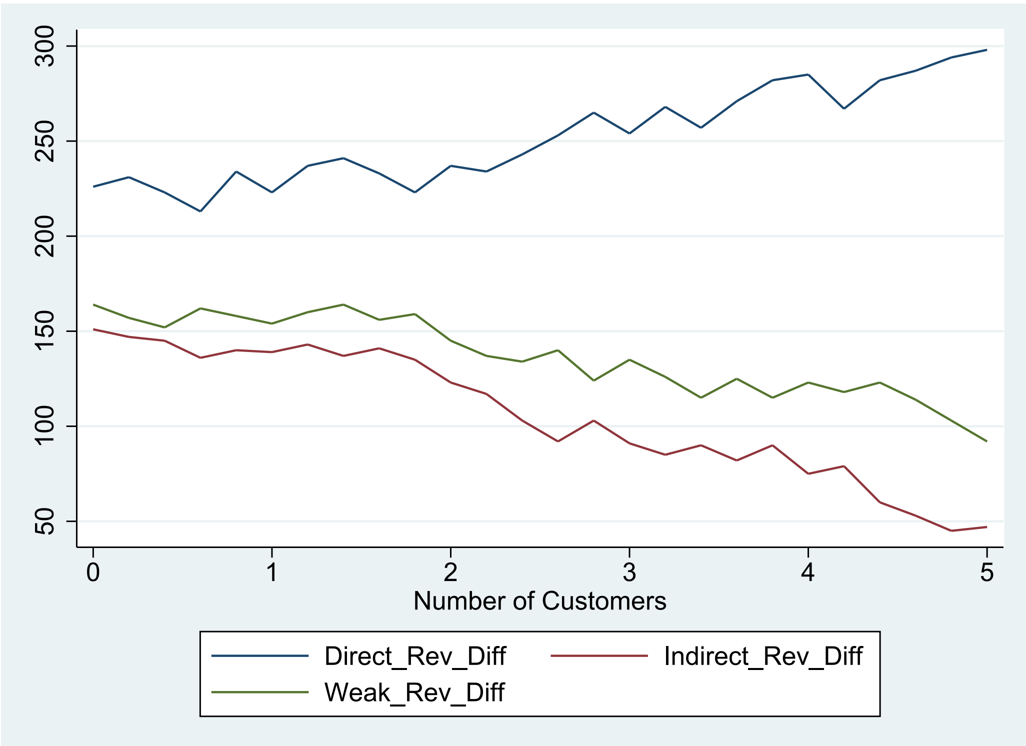
Notes: Data source: Capital IQ

Figure 3.20: Revenue Differences of Target Firms



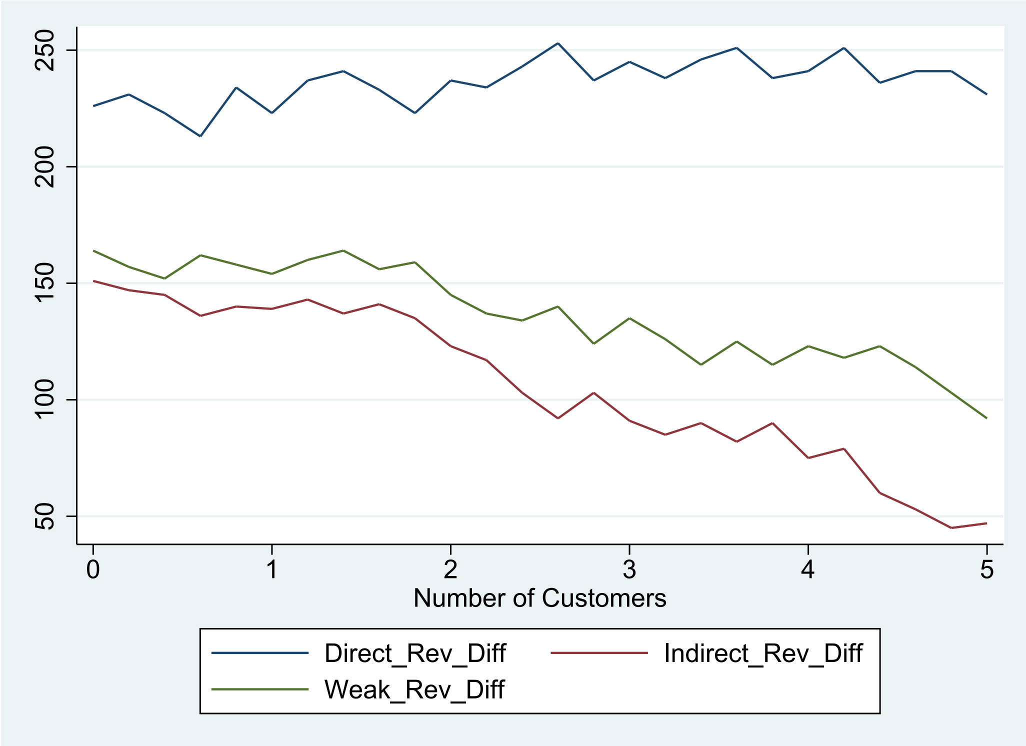
Notes: Data source: Capital IQ

Figure 3.21: Revenue Differences of Target Firms



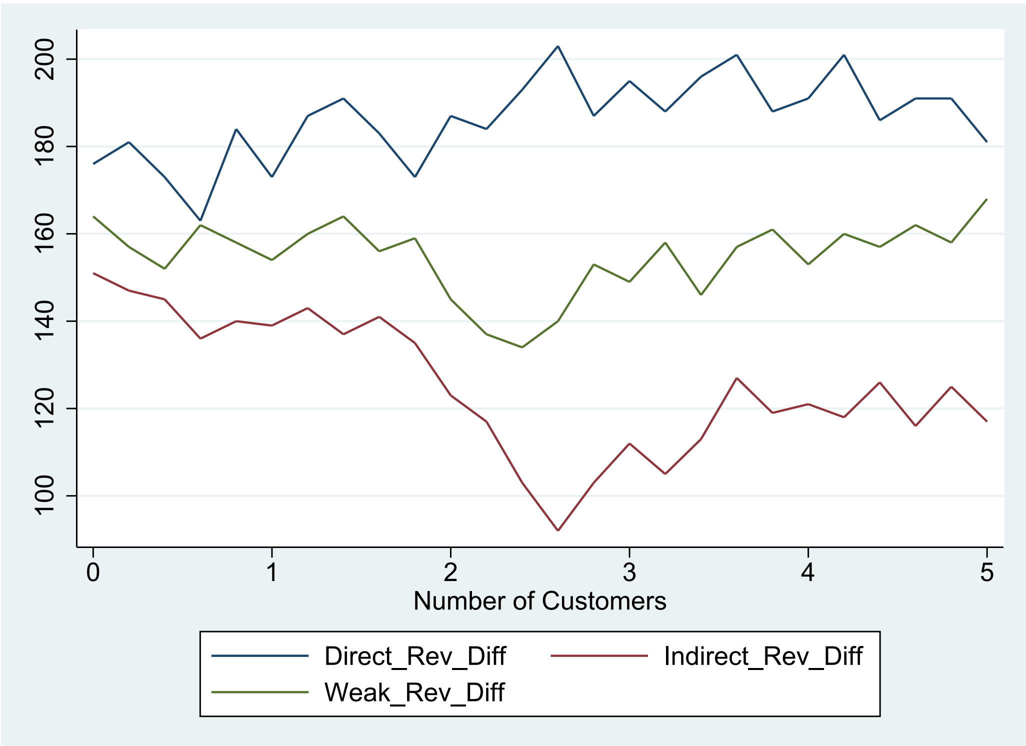
Notes: Data source: Capital IQ

Figure 3.22: Revenue Differences of Target Firms



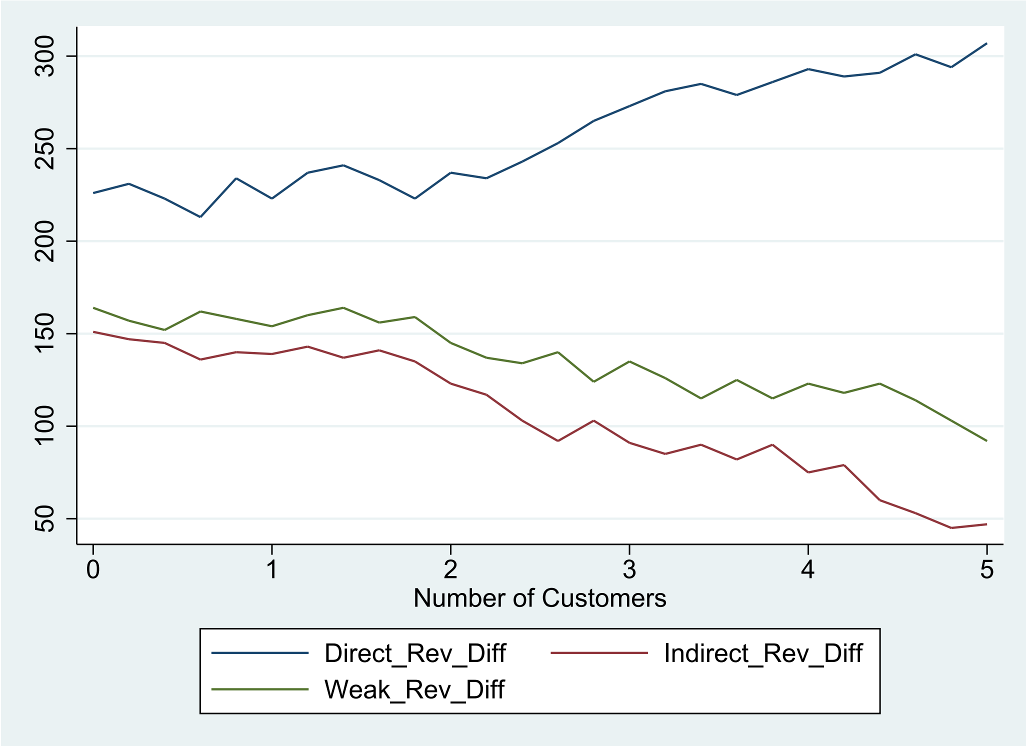
Notes: Data source: Capital IQ

Figure 3.23: Revenue Differences of Target Firms



Notes: Data source: Capital IQ

Figure 3.24: Revenue Differences of Target Firms



Notes: Data source: Capital IQ

Figure 3.25: Revenue Differences of Target Firms

3.7 Conclusion

This paper studies how idiosyncratic shocks propagate to aggregate level using firm-level data. Sectoral asymmetry, or "influential matrix", can be calculated using input-output table. However, firm-level influential matrix is very difficult, even impossible, to calculate with available data. Then, how can we investigate propagation of firm-level shocks? In order to answer this question, we focus on shocks that have been proved to correlate with business cycle and explore why they propagate. To identify firm level shocks, different from past literatures, we use mergers and acquisitions (M&A).

According to our estimations, we find that M&A has a short-term positive effect on revenues and a prolonged positive effect on productivities of target firms. It increases firms' revenues by around 10%, and productivities by about 3%. Out of consideration on endogeneity issue, we use both difference-in-difference (DID) and instrument variable (IV) method. DID method compares the firms performances ex ante and ex post. The control group is built up by firms having M&As later than the treated group. By doing this, we avoid the potential endogeneity problem that M&A decision depends on unobserved variables of the target firms. However, the endogenous timing of M&As cannot be solved. The instrument variable is constructed as merger arbitrage spread. Mergers trade at a discount because there always an uncertainty that a deal will break. The merger arbitrage spread captures this risk of M&A. It is correlated with M&A transactions, while independent of productivities. Productivities can only be changed through long term of reallocating assets or adopting of new technologies. The merger arbitrage spread is a short-term market reaction to the news of M&A. Therefore, they are not correlated.

We then trace the propagation of these shocks in production networks using a giant supplier-customer adjacency matrix which we calculate from Capital IQ data base. We find that almost every firm is connected in the supplier-customer network; and this network indeed has the asymmetry features. It can be approximated by a Type-I Pareto with a = 1.8. Here we discriminate self-M&A from supplier-M&A. The supplier-M&A refers to the M&A events happened to a firm's suppliers. Supplier-M&As are more prevalent than we expect, and of higher frequency. About 15% of firms are involved in supplier-M&As. And they have supplier-M&As happening every two years. According to our estimations, supplier-M&A increases a firm's revenues more than self-M&A by almost twice. This is very surprising if we consider that intermediate goods takes only a fraction in production function. This surprisingly large effects come from the fact that M&A combines the connections of these two firms therefore changes the distribution of "influence" of the firms. Firms involved in M&A transactions become more important because they asymmetrically supply to more customers. Therefore, the effects are amplified.

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.1 Data Description

.1.1 China Family Panel Studies (CFPS)

China Family Panel Studies (CFPS) is a nationally representative, annual longitudinal survey of Chinese communities, families, and individuals launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University, China. Up till now, three waves are available: 2010, 2012 and 2014. The CFPS is funded by the Chinese government through Peking University.

The data set covers 28 provinces in China (Anhui, Beijing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hebei, Jiangxi, Liaoing, Ningxia, Qinghai, Shandong, Shanxi, Shaanxi, Shanghai, Sichuan, Tianjin, Xinjiang, Yunnan, Zhejiang and Chongqing), with 42,790 individuals and 14,797 families in 2010; and 44,339 individuals and 13,315 families in 2012; and 45,172 individuals and 13,275 families in 2014. The follow-up rate is 93.05% and 95.12%. The sample for the 2010 CFPS baseline survey through a multi-stage probability is drawn with implicit stratification. It is designed to reduce the operational cost of the survey. Each subsample in the CFPS study is drawn through three stages: county (or equivalent), then village (or equivalently), then household. Refusal rate is 7.50%, 3.21% and 3.71% in 2010, 2012 and 2014, respectively.

Three key features of the CFPS are worth noting here: 1.All members over age 9 in a sampled household are interviewed. These individuals constitute core members of the CFPS. 2.As in the PSID, children of the CFPS are also considered core members of the CFPS. Theoretically, a core member can leave the study only through death. 3. Follow-up of all core members of the CFPS is designed to take place on a yearly basis. Five provinces are chosen for initial oversampling (1600 families in each) so that regional comparisons can be made. The remainder of the CFPS sample (8000 families) is drawn from the other provinces so as to make the overall CFPS sample representative of the country through weighting (except for remote areas, noted later).

Interviews will be conducted using computer assisted personal interviewing (CAPI) technology, provided by the Survey Research Center (SRC) at the University of Michigan. The CAPI and its associated survey-management system enables the researchers to design a fairly complex interview schedule tailored to each member of the household and reduces measurement error while at the same time allowing the management team at the ISSS to closely monitor the quality of the interviews in the field. In the 2010 baseline survey, the CFPS successfully interviewed almost 15,000 families and almost 30,000 individuals within these families, for an approximately response rate of 79%. The

CFPS respondents are tracked through annual follow-up surveys.

Four types of data are available in each year: family relationship data, family economics data, adult data and child data. The inclusion of these data provide us with a tool to ***locate each individual on his family tree and track an individual along the branch of the family tree to reach his/her parents or children***.

Some definitions are elaborated below.

Age of household: the age of the house head. Later, to control measurement error issue, I estimate individual-level variable of interests, see Appendix .2.

Young household: adult households who are below 30.

Middle-aged household: adult households who are between 30 and 60.

Elderly household: adult households who are beyond 60.

Saving rate: There are two measures of saving rates. **Measure 1** is the share of disposable income net of total expenditure in disposable income. **Measure 2** is the change of assets over disposable income (excluding capital income). In this data set, I use Measure 1 because I do not have access to detailed assets information.

Family with a loss of children: a family which experienced loss of at least one child, due to any possible reason.

Family with accidental loss of children: a family which experienced a loss of at least one child, due to the reason of disease, natural disaster, traffic accident, work accident, suicide, murder, etc. The summarization of death reason can be seen in Table **??**.

intergenerational transfers on housing: transfer of cash or any kind of assets for the purpose of acquiring a house. Co-residence is considered as a transfer from the owner to other non-spouse adult family members.

.1.2 China Household Finance Survey (CHFS)

The China Household Finance Survey (CHFS) launches nation-wide surveys in 2011, 2013 and 2015. It is founded by Southwestern University of Finance and Economics (SWUFE), directed by Li Gan.

This data covers 25 provinces in China (Anhui, Beijing, Gansu, Guangdong, Guangxi, Guizhou, Hebei, Henan, Heilongjiang, Hubei, Hunan, Jilin, Jiangsu, Liaoning, Qinghai, Shandong, Shanxi, Shaanxi, Shanghai, Sichuan, Tianjin, Yunan, Zhejiang and Chongqing), with 8,438 households and

29,463 individuals. The weighted average household size is 2.94 individuals, specifically 2.67 for urban households and 3.18 for rural households. The overall refusal rate is 11.6%. The sampling design consists of two major components: an overall sampling scheme and an on-site sampling scheme based on mapping. The overall sample scheme employs a stratified three-stage probability proportion to size (PPS) random sample design.

In the data, expenditure and income, non-financial assets, insurance and social welfare, household financial assets, intergenerational transfer and households debts are available. Zooming into expenditure and transfer, the items related to each of the houses owned by the individual are displayed in detail. This serves three purposes: first, this allows us enough freedom to estimate the life time intergenerational transfer pattern for each age group. Second, it specifies the volume of intergenerational transfer targeted on each of the house owned by the household. Third, the identity of the related bank is available, thus provide us with a tool to back out the borrowing constraint of the households.

Some definitions are elaborated below.

Saving rate: We use both Measure 1 and Measure 2. In Measure 1, saving rates is defined as :

$$Srt_t^I = 1 - \frac{Consumption_t}{DI_t}$$

Consumption is the sum of all types of consumer spending, including daily use expenditure, transport costs, clothing, housing maintenance . where DI represents disposable income. In Measure 2, saving rate is defined as

$$Srt_t^{II} = \frac{Asset_t - Asset_{t-1}}{DI_t}$$

$Asset_t$ refers to the net asset level, which is assets net of debts. Assets include all types of financial assets: demand deposits, time deposit (certificates of deposits), stocks, bonds, funds, derivatives, financial products, non-RMB denominated assets, gold, cash . Debts include student loans, credit cards .

.2 Correcting Measurement Error of Saving Rates

Deaton and Paxson (2000), Choukhmane et al. (2016) and Rosenzweig and Zhang (2015) have shown in their paper the problems associated with using the household approach to construct age-saving profiles in the presence of multi-generational households. In China, co-residence of different generations is not rare, see Foster and Rosenzweig (2001). Table 17 display the composition of Chinese family. If a distinctive fraction of households in the family are at different life-cycle stages from the households heads, the age-saving profile will be obscured. There might be two potential bias if I count ages of households by their heads.

Table 17: Summary Statistics of Family Composition

House Head	Generation Structure	Percentage	Average Age
Young	uni-generation	7.24%	24.37
($Age < 30$)	multi-generation	2.37%	40.58
Middle-Aged	uni-generation	31.15%	49.71
($30 \leq Age < 60$)	multi-generation	33.31%	45.12
Old	uni-generation	15.61%	71.21
($Age \geq 60$)	multi-generation	10.23%	58.12
Sample Size	61,423		

Note: Data source is CFPS (2010, 2012).

First, the bias could arise from selection. Young and old individuals are unlikely to become household heads. If the young and old are selected to be household heads, this implies that these young and old individuals might live independently from their parents or children. These people tend to be richer. And richer individuals tend to have higher saving rates. Therefore, I suffer from over-estimating saving rates of the young and elderly. Table 18 displays the average income of young and old individuals who are households heads and those who are not. We observe from the table that young and old individuals who are households have much higher income and saving rates than their counterparts.

Table 18: Features of Young/Old Individuals Being Head and Non-Head

	Head			**Non-Head**		
Young Individuals						
Variable	Mean	Min	Max	Mean	Min	Max
Age	24.9	20	30	25.1	20	30
Male	0.53	0	1	0.58	0	1
Urban	0.68	0	1	0.53	0	1
Han	0.63	0	1	0.57	0	1
Married	0.85	0	1	0.21	0	1
Siblings	1.1	0	3	1.2	0	2
Yeas of Employment	3.7	0	8	4.2	0	9
Income	28,953	0	613,843	12,171	0	127,465
Saving Rates (%)	23.15	3.7	32.56	8.91	0	24.19
Elderly Individuals						
Variable	Mean	Min	Max	Mean	Min	Max
Age	65.73	61	87	67.17	61	91
Male	0.51	0	1	0.56	0	1
Urban	0.71	0	1	0.67	0	1
Han	0.58	0	1	0.60	0	1
Married	0.82	0	1	0.53	0	1
Siblings	3.1	0	5	2.7	0	6
Yeas of Employment	31.7	0	37	30.8	0	35
Income	17,325	0	98,425	9,435	0	71,823
Saving Rates (%)	36.15	10.3	45.56	17.13	0	31.19

Second, suppose that middle-aged individuals have high saving rates as they save for retirement, but middle-aged households heads live with younger adults or elderly members who have much lower saving rates. If I count the age by the age of middle-aged members, and count the saving rates by saving rates of the family. We have downward bias of the middle-aged. Table 19 display the features of uni-generation middle-aged families against the multi-generation middle-aged families. We observe that uni-generation families have higher income and higher saving rates than the uni-generation families.

Table 19: Features of Middle-aged Individuals Being Head and Non-Head

	Uni-generation			**Multi-generation**		
Variable	Mean	Min	Max	Mean	Min	Max
Age	47.1	31	60	48.5	31	60
Male	0.47	0	1	0.51	0	1
Urban	0.62	0	1	0.63	0	1
Han	0.61	0	1	0.67	0	1
Married	0.87	0	1	0.73	0	1
Siblings	3.7	0	5	4.1	0	5
Yeas of Employment	27.7	0	27	24.2	0	29
Income	79,173	0	612,372	63,562	0	673,001
Saving Rates (%)	37.25	24.58	41.00	35.12	30.81	32.19

To solve this problem, I follow the method of Choukhmane et al. (2016). To be brief, I estimate individual consumption using nonlinear least square (NLLS) method. And then calculate individual saving rates using the estimated consumption and individual income directly from the data set. Household consumption is the sum of individual consumption, and is observable. k represents family, and i represents individual.

$$\mathbb{C}_k = \sum_i c_{k,i}$$

We assume that individual consumption $c_{k,i} = F(\mathbb{Z}_k) \cdot c_a$. $\mathbb{Z}_k$ is family level characteristics. c_a is age-related consumption. We make the key assumption that c_a is identical across individuals and families, given the same age a. Following Choukhmane et al. (2016), I assume the F function takes the exponential form. Therefore, I have the following expression for household-level consumption:

$$\mathbb{C}_k = \sum_a N_{k,a} \cdot exp(\gamma \mathbb{Z}_k) \cdot c_a \tag{9}$$

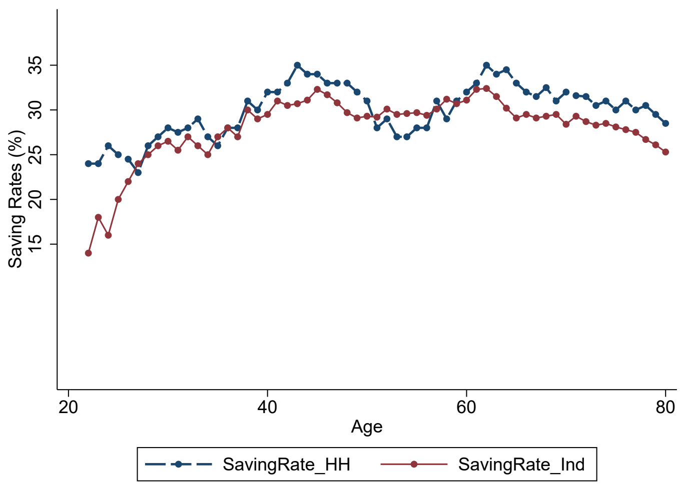
where $N_{k,a}$ is the number of individuals with age a inside family k. The control variables include: urban/rural, number of members, the fraction of young, middle-aged, old; household income group, etc. The NNLS estimator satisfies the following:

$$\{\hat{\gamma}, \hat{c_a}\} = arg \min_{\{\tilde{\gamma}, \tilde{a}\}} \mathbb{C}_k = \sum_a N_{k,a} \cdot exp(\tilde{\gamma} \mathbb{Z}_k) \cdot \tilde{c_a} \tag{10}$$

In this equation, $\mathbb{C}_k$, $N_{k,a}$, $\mathbb{Z}_k$ are all observables. With the estimator $\hat{\gamma}$ and $\hat{a}$, I can calculate the individual consumption following the equation:

$$\hat{c}_{k,i} = exp(\hat{\gamma} \mathbb{Z}_k) \cdot \hat{c_a} \tag{11}$$

Therefore, I could calculate the age-saving profile using individual consumption and income. Figure 26 displays the age-saving profile. We observe that compared to the estimation, the data indeed have upward bias for young and elderly households, and downward bias for the middle-aged households, except for households whose age are more than 72. We expect the elderly households suffer from upward bias, however households older than 72 have downward bias. One explanation is these elderly households are not uni-generation households as I discussed above. They are multi-generation households: elderly parents living with middle-aged children, or elderly grand parents living with young grand children, or the mixture. In this case, the middle-aged children or the young grand children have lower income thus lower saving rates than the elderly, since the elderly members are households heads. Table 17 shows that the fraction of this kind of family is 10.23%, which is large compared to multi-generation family with young households heads. Therefore, the household approach could lead to downward bias. To validate this supposition, I display the features of multi-generation family with elderly household heads in Table 20. The reason I have access to part of the individual information for these families is that the CFPS asks question about change of family members. For example, it investigates whether each family member live in the family for a given year, how long are they away from the family, are there new family members to join? Are they new born babies, through marriage, or through adoption, etc. This information allow us to estimate the individual consumption by differencing the consumption level with or without certain family members.



Notes: Data source: CFPS

Figure 26: Age-Saving Profile: Data and Estimation

Table 20: Features of Middle-aged Individuals Being Head and Non-Head

	Multi-Generation Families with Elderly Heads			**Other Multi-generation Families**		
Variable	Young	Middle-aged	Old	Young	Middle-age	Old
Age	23.7	45.2	67.8	24.1	47.2	68.3
Urban	0.53	0.56	0.57	0.57	0.61	0.55
Married	0.17	0.85	0.85	0.33	0.86	0.83
Income	9,221	49,435	358,372	17,562	87,321	73,001
Saving Rates (%)	5.25	23.58	37.32	17.58	30.81	32.19
Sample Size		6,923			7,510	

.3 Theoretical Appendix

.3.1 Three period OLG Model

$$\max_{c,a,H,T} V_{y,t} = U_{y,t} + \lambda U_{y,t+1} + \mu U_{y,t-1}$$

$$\text{s.t.} \qquad c_{y,t} + a_{y,t} + P_t H_t \leq w_{y,t} + T_{y,t}$$

$$c_{m,t+1} + a_{m,t+1} + T_{y,t+1} + T_{o,t+1} \leq w_{m,t+1} + Ra_{y,t}$$

$$c_{o,t+2} \leq T_{o,t+2} + Ra_{m,t+1}$$

The F.O.Cs are:

$$c_{y,t} = \frac{1}{\lambda_t}$$

$$c_{m,t+1} = \frac{\beta}{\lambda_{t+1}}$$

$$c_{o,t+2} = \frac{\beta^2}{\lambda_{t+2}}$$

$$P_t H_t (1-\rho)\lambda_t = \kappa(1+\beta+\beta^2)$$

$$\lambda_t = \lambda \cdot \frac{1}{c_[y, t+1]}$$

$$\lambda_t = \mu \cdot \frac{\beta^2}{c_{o,t+1}}$$

where $c_{y,t+1}$ is the consumption of the children, and $c_{o,t+1}$ is the consumption of the parents. Rearranging the terms, I end up with the equations:

$$c_{y,t} = \frac{w_{y,t} + T_{y,t}}{1+\kappa(1+\beta+\beta^2)}$$

$$P_t H_t = \frac{\kappa(1+\beta+\beta^2)}{(1-\rho)[1+\kappa(1+\beta+\beta^2)]} \cdot \left(w_{y,t} + T_{y,t}\right)$$

$$c_{m,t+1} = \frac{1}{1+\beta}\left(w_{m,t+1} - \mu w_{y,t} + (\frac{T_{o,t+2}}{R} - T_{y,t+1} - T_{o,t+1})\right)$$

$$c_{o,t+2} = \frac{\beta R}{1+\beta}\left(w_{m,t+1} - \mu w_{y,t} + (\frac{T_{o,t+2}}{R} - T_{y,t+1} - T_{o,t+1})\right)$$

$$T_{y,t+1} = \frac{R}{\mu(R+1)} T_{y,t} + \frac{\rho R}{(1-\rho)(1+R)} \cdot \frac{M_t}{\mu} - \frac{\rho}{1-\rho} \cdot M_{t+1} \tag{12}$$

$$T_{o,t+2} = \left(1 + \frac{1}{(R+1)\mu}\right) T_{o,t+1} - \frac{R}{(R+1)\mu} T_{o,t} + Z_{t,t+1} \tag{13}$$

where M_t and $Z_{t,t+1}$ are defined as the following:

$$M_t = \frac{1-\rho+\mu}{\rho} w_{y,t} - \mu w_{y,t-1}$$

$$\rho = \frac{(1+\kappa)\lambda}{\beta(1+\beta)+(1+\kappa)\lambda}$$

$$Z_{t,t+1} = \frac{R}{(R+1)\mu}\left(w_{m,t} + \frac{M_t}{1-\rho} - \frac{(1-\rho+\mu)w_{y,t}}{\rho}\right) - \left(w_{m,t+1} + \frac{M_{t+1}}{1-\rho} - \frac{(1-\rho+\mu)w_{y,t+1}}{\rho}\right)$$

$$Y_t = (1-\rho+\mu)w_{y,t}$$

$$\begin{aligned} c_{m,t+1} =& \frac{R(w_{m,t+1} - T_{o,t+1} - T_{y,t+1}) + T_{o,t+2}}{R(1+\beta)} \\ &+ \frac{\kappa\rho R(1+\beta+\beta^2)}{(1-\rho)(1+\beta)[1+\kappa(1+\beta+\beta^2)]}(w_{y,t} + T_{y,t}) \end{aligned} \tag{14}$$

In this formula, middle-aged consumption $c_{m,t+1}$ is positively correlated with income in each period, while not being proportional to the life-time wealth, as classical log-utility OLG model predicts. The reason is that credit constraint ($a_{y,t} \leq -\rho P_t H_{y,t}$) cuts the link of shadow prices between period t and period $t+1$ for cohort (y,t). Therefore, middle-aged consumption $c_{m,t+1}$ is not proportional to young-aged consumption $c_{y,t}$ with the coefficient of βR. If the young households are not subject to the credit constraints, borrowing amount $a_{y,t}$ will shoot up to the level which makes the ratio of shadow price in period t to the shadow price in period $t+1$ equalized to interest rate R.

$$\begin{aligned} s_{y,t} &= a_{y,t} + P_t H_{y,t} \\ &= \frac{\kappa(1-\rho)(1+\beta+\beta^2)}{1+\kappa(1-\rho)(1+\beta+\beta^2)} \cdot (w_{y,t} + T_{y,t}) \end{aligned} \tag{15}$$

$$\begin{aligned} s_{o,t+2} =& -\frac{R\beta(w_{m,t+1} - T_{y,t+1} - T_{o,t+1})}{1+\beta} + \frac{T_{o,t+2}}{1+\beta} \\ &+ \frac{\kappa\rho\beta R(1+\beta+\beta^2)}{(1-\rho)(1+\beta)[1+\kappa(1+\beta+\beta^2)]}(w_{y,t} + T_{y,t}) \end{aligned} \tag{16}$$

The saving of young household is the sum of two terms: savings on risk-free assets $a_{y,t}$ and housing assets $P_t H_{y,t}$. $s_{y,t}$ is positively correlated with the transfers they receive $T_{y,t}$. And it increases with the tightness of credit constraints ρ. The former is straightforward, since the more they receive, the more they save. The latter stems from the fact that tight credit constraints prevent households from over-borrowing. It not only prevents the young from borrowing a high fraction of housing value (not more than ρ), but also discourages the young to buy expensive houses $P_t H_{y,t}$. This is because young households will expect it to be difficult to borrow money for a house out of their reach.

The last two equations are law of motion of transfers to the young and transfer to the old. Plug these into the definition of saving rates Definition 1, I end up with saving rates for the young, middle-aged and old households, displayed in equation 15, equation 1.9 and equation 16.

Proposition 1: Saving rates of the middle-aged decreases with altruism and the tightness of borrowing constraint:

$$\frac{\partial s_{m,t}}{\partial \lambda} < 0, \frac{\partial s_{m,t}}{\partial \mu} < 0$$

$$\frac{\partial s_{m,t}}{\partial \mu} > 0, \frac{\partial s_{m,t}}{\partial \mu} > 0$$

Proof: The proof for the two altruistic parameters λ and μ are the same. Therefore, I only display the proof of $\frac{\partial s_{m,t}}{\partial \lambda} < 0$. From equation 1.9, it is able to figure out that altruism has an effect on $s_{m,t+1}$ through the intergenerational transfer term $\frac{T_{o,t+2}}{w_{m,t+1}R} - \beta \frac{T_{y,t+1} + T_{o,t+1}}{w_{m,t+1}}$, therefore, I rearrange this term to derive the partial differentiation $\frac{\partial s_{m,t+1}}{\partial \lambda}$.

$$\begin{aligned}\frac{T_{o,t+2}}{w_{m,t+1}R} - \beta \frac{T_{y,t+1} + T_{o,t+1}}{w_{m,t+1}} = & \frac{1}{Rw_{m,t+1}}((1-\beta\rho)T_{o,t+2} - \beta(1-\rho)T_{o,t+1}) \\ & + \beta\left(\rho - \frac{Y_{t+1}}{w_{m,t+1}}\right)\end{aligned}$$

Plug equation 13 into the equation above:

$$\begin{aligned}\frac{T_{o,t+2}}{w_{m,t+1}R}-\beta\frac{T_{y,t+1}+T_{o,t+1}}{w_{m,t+1}}=&\frac{1}{Rw_{m,t+1}}\left(\frac{(1-\beta)(1+\mu+\mu R)+(1-R(1-\beta R))}{(R+1)\mu}+\frac{1-\beta\rho}{(R+1)^2\mu^2}\right)T_{o,t}\\&-\left(\frac{(1-\beta)R}{(R+1)\mu}+\frac{(1-\beta\rho)R}{(R+1)^2\mu^2}\right)T_{o,t-1}\\&+\left(\left(1-\beta+\frac{1-\beta\rho}{(R+1)\mu}\right)Z_{t-1,t}+(1-\beta\rho)Z_{t,t+1}\right)\end{aligned}$$

From the law of motion of transfers, equation 12 and equation 13, I know that transfers are linked, therefore, the partial differentiation equals to:

$$\begin{aligned}\frac{\partial s_{m,t+1}}{\partial\lambda}&=\frac{1}{w_{m,t+1}R}\cdot\frac{\partial T_{o,t+2}}{\partial\lambda}-\frac{\beta}{w_{m,t+1}}\cdot\frac{\partial(T_{y,t+1}+T_{o,t+1})}{\partial\lambda}\\&=\frac{1}{Rw_{m,t+1}}\left(\frac{\partial((1-\beta\rho)T_{o,t+2}-\beta(1-\rho)T_{o,t+1})}{\partial\lambda}\right)+\beta\frac{\partial\left(\rho-\frac{Y_{t+1}}{w_{m,t+1}}\right)}{\partial\lambda}\end{aligned}$$

By simple algebra, it is able to obtain the partial differentiation:

$$\begin{aligned}\frac{\partial s_{m,t+1}}{\partial\lambda}=&\{-\frac{\beta T_{o,t}}{(R+1)^2\mu^2}-\frac{R\beta T_{o,t-1}}{(R+1)\mu^2}+(1+\frac{w_{y,t}}{w_{m,t+1}})\\&+\frac{(R+1)\mu(\beta-1)(R(1+\rho)(1+\mu)-\rho\mu)(1+\omega+\omega^2)+R(1-\rho+\mu)(1-\beta\rho^2)}{\rho(1-\rho)^2(R+1)^2\mu^2}w_{y,t-1}\\&-\frac{\beta(R+1)\mu(1-\mu^2)-(1+\mu)(\beta R(R-1)+1)}{\rho(1-\rho)(R+1)\mu}\}\cdot\frac{\partial\rho}{\partial\lambda}\end{aligned}$$

where $\rho=\frac{(1+\kappa)\lambda}{\beta(1+\beta)+(1+\kappa)\lambda}$. Here I assumer that $\frac{w_t}{w_{t-1}}=\omega$, for all t. It is straightforward that the bracket is negative, and the partial differentiation $\frac{\partial\rho}{\partial\lambda}$ is positive. So that $\frac{\partial s_{m,t+1}}{\partial\lambda}$ is negative.

Then I prove that $\frac{\partial s_{m,t}}{\partial\mu}>0$. From equation 1.9:

$$s_{m,t+1}=\frac{\beta}{1+\beta}(1-\frac{\mu Rw_{y,t}}{w_{m,t+1}})+\frac{1}{1+\beta}\left(\frac{T_{o,t+2}}{w_{m,t+1}R}-\beta\frac{T_{y,t+1}+T_{o,t+1}}{w_{m,t+1}}\right)$$

the partial differentiation of saving rate on μ is:

$$\frac{\partial s_{m,t}}{\partial\mu}=-\frac{R\beta w_{y,t-1}}{(1+\beta)w_{m,t}}+\frac{1}{(1+\beta)w_{m,t}}\left(\frac{1}{R}\cdot\frac{\partial T_{o,t+1}}{\partial\mu}-\beta\cdot\frac{\partial(T_{o,t}+T_{y,t})}{\partial\mu}\right)$$

Plugging equation 13 into the above equation gives us:

$$\begin{aligned}\frac{\partial s_{m,t}}{\partial \mu} =& \frac{(R+1)\mu(1-\beta R(1-\rho))+1}{(R+1)^2\mu^2(1-\rho)} \cdot w_{y,t-2} \\ &+ \left(\left(1+\frac{1}{R(R+1)\mu}-\beta\right)\cdot\frac{R}{R(R+1)\mu}+\beta+\frac{1-\beta R}{(R+1)\mu(1-\rho)}\right)\cdot w_{y,t-1} \\ &+ \left(\frac{1+(1-\mu)/R+\mu(R+\rho-1)}{(R+1)\mu(1-\rho)}+\beta\right)\cdot w_{y,t}\end{aligned} \tag{17}$$

As long as $\beta R < 1$, e bracket is positive. Therefore, $\frac{\partial s_{m,t}}{\partial \mu}$ is positive. The role of housing prices are the same with borrowing constraint in the three-period model. We prove the proposition hold in the multi-period version.

.3.2 Multi-period Model

$$\max_{c,a,H,T} V_{y,t} = U_{y,t} + \lambda U_{y,t+3} + \mu U_{y,t-3}$$

where $U_{y,t} = \sum_{\tau=0}^{5} \beta^{\tau} u_{y,t+\tau}$, and $u = log(c) + \kappa log(H)$.

$$\text{s.t.} \qquad c_{y,t} + a_{y,t} \leq w_{y,t} + T_{y,t}$$

$$c_{y,t+1} + a_{y,t+1} + P_{t+1}H_{y,t+1} \leq w_{y,t+1} + Ra_{y,t} + T_{y,t+1}$$

$$c_{m,t+2} + a_{m,t+2} + T_{y,t+2} + T_{o,t+2} \leq w_{m,t+2} + Ra_{y,t+1}$$

$$c_{m,t+3} + a_{m,t+3} + T_{y,t+3} + T_{o,t+3} \leq w_{m,t+3} + Ra_{m,t+2}$$

$$c_{o,t+4} + a_{o,t+4} \leq w_{m,t+4} + Ra_{m,t+3} + T_{o,t+4}$$

$$c_{o,t+5} \leq Ra_{m,t+4} + T_{o,t+5}$$

And savings are defined as disposable income net of consumption, or change of assets levels. These two definitions are equivalent as shown below.

$$S_{y,t} = w_{y,t} + T_{y,t} - c_{y,t} = a_{y,t}$$

$$S_{y,t+1} = w_{y,t+1} + T_{y,t+1} - c_{y,t+1} = a_{y,t+1} + P_{t+1}H_{y,t+1} - Ra_{y,t}$$

$$S_{m,t+2} = w_{m,t+2} - T_{o,t+2} - T_{y,t+2} - c_{m,t+2} = a_{m,t+2} - Ra_{y,t+1}$$

$$S_{m,t+3} = w_{m,t+3} - T_{o,t+3} - T_{y,t+3} - c_{m,t+3} = a_{m,t+4} - Ra_{m,t+3}$$

$$S_{o,t+4} = w_{o,t+4} + T_{o,t+4} - c_{o,t+4} = a_{o,t+4} - Ra_{m,t+3}$$

$$S_{o,t+5} = T_{o,t+5} - c_{o,t+5} = -Ra_{m,t+4}$$

Therefore, saving rates can be defined as:

$$s_{y,t} = 1 - \frac{c_{y,t}}{w_{y,t} + T_{y,t}}$$

$$s_{y,t+1} = 1 - \frac{c_{y,t}}{w_{y,t+1} + T_{y,t+1}}$$

$$s_{m,t+2} = 1 - \frac{c_{m,t+2}}{w_{m,t+2} - T_{y,t+2} - T_{o,t+2}}$$

$$s_{m,t+3} = 1 - \frac{c_{m,t+3}}{w_{m,t+3} - T_{y,t+3} - T_{o,t+3}}$$

$$s_{o,t+4} = 1 - \frac{c_{o,t+4}}{w_{o,t+4} + T_{o,t+4}}$$

$$s_{o,t+5} = 1 - \frac{c_{o,t+5}}{T_{o,t+5}}$$

The first order conditions (F.O.Cs) are:

$$c_{t+\tau} : c_{t+\tau} = \frac{\beta^{\tau}}{\lambda_{t+\tau}} \tag{18}$$

for $\tau = 0, 1, 2, 3, 4, 5$.

$$a_{t+\tau} : \lambda_{t+\tau} = R\lambda_{t+\tau+1} \tag{19}$$

for $\tau = 0, 2, 3, 4$

$$a_{y,t+1} : a_{y,t+1} = \mu \cdot \rho P_{t+1} H_{y,t+1} \tag{20}$$

$$H_{y,t+1} : P_{t+1} H_{y,t+1} = \frac{\kappa \sum_{t=1}^{6} \beta^{t-1}}{1-\rho} \cdot c_{y,t+1} \tag{21}$$

$$T_{y,t+2} : \frac{1}{c_{m,t+2}} = \lambda \cdot \left[\frac{1+\beta}{(1+\beta+m)c_{y,t+2}} - \frac{R^2 \beta \rho m}{(1+\beta+m)c_{m,t+4}} \right] \tag{22}$$

$$T_{y,t+3} : \frac{1}{c_{m,t+3}} = \lambda \cdot \left[\frac{1+\beta}{(1+\beta+m)c_{y,t+3}} - \frac{R^2 \beta \rho m}{(1+\beta+m)c_{m,t+5}} \right] \tag{23}$$

$$T_{o,t+2} : \frac{1}{c_{m,t+2}} = \frac{\beta^2 \mu}{R^2 c_{m,t}} \tag{24}$$

$$T_{o,t+2} : \frac{1}{c_{m,t+3}} = \frac{\beta^2 \mu}{R^2 c_{m,t+1}} \tag{25}$$

Now I further assume that parents only care about the utility of their children when they are young, to simplify our model. Rearranging Equation 22 and Equation 24, I have:

$$c_{m,t+2} = \frac{1+\beta+m}{\lambda(1+\beta)} c_{y,t+2} \tag{26}$$

$$c_{m,t+2} = \frac{R^4}{\mu} c_{o,t+2} \tag{27}$$

Budget Constraint leads to:

$$Rc_{y,t} + c_{y,t+1} + a_{y,t+1} + P_{t+1}H_{y,t+1} = Rw_{y,t} + RT_{y,t} + w_{y,t+1} + T_{y,t+1} \tag{28}$$

Together with F.O.C. 21, F.O.C. 19 and F.O.C. 18, I have:

$$c_{y,t} = \frac{1}{1+\beta+m}(w_{y,t} + T_{y,t}) + \frac{1}{(1+\beta+m)R}(w_{y,t+1} + T_{y,t+1}) \tag{29}$$

where $m = \frac{\kappa}{1-\rho}\sum_{t=1}^{6}\beta^t$. Together with budget constraint, I have:

$$S_{y,t} = \frac{\beta+m}{1+\beta+m}(w_{y,t} + T_{y,t}) + \frac{1}{1+\beta+m}(w_{y,t+1} + T_{y,t+1}) \tag{30}$$

Together with F.O.C. 18, I have:

$$c_{y,t+1} = \frac{\beta R}{1+\beta+m}(w_{y,t} + T_{y,t}) + \frac{\beta}{1+\beta+m}(w_{y,t+1} + t_{y,t+1}) \tag{31}$$

Therefore,

$$S_{y,t+1} = \frac{(1-\rho)m - 1}{1+\beta+m}(w_{y,t+1} + T_{y,t+1}) - \frac{(2+\beta+\beta m)R}{1+\beta+m}(w_{y,t} + T_{y,t}) \tag{32}$$

Together with F.O.C. 21 and Equation 29, I also have:

$$P_{t+1}H_{y,t+1} = \frac{\beta m R}{1+\beta+m}(w_{y,t} + T_{y,t}) + \frac{\beta m}{1+\beta+m}(w_{y,t+1} + T_{y,t+1}) \tag{33}$$

Then I move to the next period. From budget constrains, I have:

$$\begin{aligned} R^3(\sum_{t=1}^{4}\beta^{t-1})c_{m,t+2} + R^3(T_{y,t+2} + T_{o,t+2}) + R^2(T_{y,t+3} + T_{o,t+3}) = \\ R^3 w_{m,t+2} + R^4 a_{y,t+1} + R^2 w_{m,t+3} + R w_{m,t+4} + RT_{o,t+4} + T_{o,t+5} \end{aligned} \tag{34}$$

Therefore, I derive $c_{m,t+2}$:

$$c_{m,t+2} = \frac{1}{R^3 \cdot \sum_{t=1}^{4}\beta^{t-1}} \cdot \left[S_t - R^2(T_{y,t+3} + RT_{y,t+2}) - R^2(T_{o,t+3} + RT_{o,t+2})\right] \tag{35}$$

where $S_t = R^3 w_{m,t+2} + R^4 a_{y,t+1} + R^2 w_{m,t+3} + R w_{m,t+4} + RT_{o,t+4} + T_{o,t+5}$. Together with the budget constraint, I have:

$$\begin{aligned}a_{m,t+2} =&(1+\frac{1}{\sum_{t=1}^{4}\beta^{t-1}})\left(w_{m,t+2}-\rho RP_{t+1}H_{y,t+1}-T_{y,t+2}-T_{o,t+2}\right)\\&+\frac{1}{R^3\sum_{t=1}^{4}\beta^{t-1}}\left[R^2w_{m,t+3}+Rw_{m,t+4}+RT_{o,t+4}+T_{o,t+5}-R^2(T_{y,t+3}+T_{o,t+3})\right]\end{aligned} \tag{36}$$

Together with F.O.C. 20, I derive $s_{m,t+2}$:

$$\begin{aligned}S_{m,t+2} =& \left(1+\frac{1}{\sum_{t=1}^{4}\beta^{t-1}}\right)(w_{m,t+2}-T_{y,t+2}+T_{o,t+2})\\&+\frac{1}{R^3\sum_{t=1}^{4}\beta^{t-1}}\left[R^2w_{m,t+3}+Rw_{m,t+4}+RT_{o,t+4}+T_{o,t+5}-R^2(T_{y,t+3}+T_{o,t+3})-\rho R^4P_{t+1}H_{y,t+1}\right]\end{aligned} \tag{37}$$

From the F.O.C.s of consumptions, I have:

$$c_{m,t+3}=\frac{1}{R^2\sum_{t=1}^{4}\beta^{t-2}}\cdot\left[S_t-R^2(T_{y,t+3}+RT_{y,t+2})-R^2(T_{o,t+3}+RT_{o,t+2})\right] \tag{38}$$

$$c_{o,t+4}=\frac{1}{R\sum_{t=1}^{4}\beta^{t-3}}\cdot\left[S_t-R^2(T_{y,t+3}+RT_{y,t+2})-R^2(T_{o,t+3}+RT_{o,t+2})\right] \tag{39}$$

$$c_{o,t+5}=\frac{1}{\sum_{t=1}^{4}\beta^{t-4}}\cdot\left[S_t-R^2(T_{y,t+3}+RT_{y,t+2})-R^2(T_{o,t+3}+RT_{o,t+2})\right] \tag{40}$$

Together with budget constraints, I can derive the asset level:

$$\begin{aligned}a_{m,t+3} =&K_1(w_{m,t+2}+\rho RP_{t+1}H_{y,t+1})+\frac{K_2}{R^2}(Rw_{m,t+3}+w_{o,t+4})\\&-K_1(T_{y,t+2}+T_{o,t+2})-(K_2+1)(T_{y,t+3}+T_{o,t+3})+\frac{K_2}{R^2}(RT_{o,t+4+T_{o,t+5}})\end{aligned} \tag{41}$$

where $K_1=\dfrac{1-\beta R}{\sum_{t=1}^{4}\beta^{t-1}}-1$, $K_2=\dfrac{1-\beta}{\sum_{t=1}^{4}}$.

$$\begin{aligned}a_{o,t+4} =&-\frac{R^3}{\sum_{t=1}^{4}\beta^{t-4}}(w_{m,t+2}-\rho RP_{t+1}H_{y,t+1})-\frac{R}{\sum_{t=1}^{4}\beta^{t-4}}(Rw_{m,t+3}+w_{o,t+4})\\&+\frac{R^3}{\sum_{t=1}^{4}\beta^{t-4}}(T_{o,t+2}+RT_{y,t+2})+\frac{R^2}{\sum_{t=1}^{4}\beta^{t-4}}(T_{o,t+3}+T_{y,t+3})\\&-\frac{R}{\sum_{t=1}^{4}\beta^{t-4}}T_{o,t+4}+(1-\frac{1}{\sum_{t=1}^{4}\beta^{t-4}})T_{o,t+5}\end{aligned} \tag{42}$$

Therefore, I derive the savings for period $t+3$, $t+4$ and $t+5$:

$$\begin{aligned} S_{m,t+3} =& K_3(w_{m,t+2} + \rho R P_{t+1} H_{y,t+1}) - K_4(R w_{m,t+3} + w_{o,t+4}) \\ & - K_3(T_{y,t+2} + T_{o,t+2}) + (RK_4 - 1)(T_{y,t+3} + T_{o,t+3}) - \frac{K_4}{R}(RT_{o,t+4+T_{o,t+5}}) \end{aligned} \tag{43}$$

where $K_3 = \frac{1-\beta R - R}{\sum_{t=1}^{4} \beta^{t-1}} + 1 - R$, $K_4 = \frac{\beta}{\sum_{t=1}^{4} \beta^{t-1}}$.

$$\begin{aligned} S_{o,t+4} =& R w_{m,t+2}(1 - \frac{1\beta R + R^2\beta^3}{\sum_{t=1}^{4} \beta^{t-1}}) + \rho R^2 P_{t+1} H_{y,t+1}(\frac{R^2\beta^3 - 1 + \beta R}{\sum_{t=1}^{4} \beta^{t-1}} + 1) \\ & - (R w_{m,t+3} + w_{m,t+4}) \cdot \frac{R\beta^3 + \beta - 1}{\sum_{t=1}^{4} \beta^{t-1}} + (T_{o,t+2} + RT_{y,t+2})(\frac{1 - \beta R + R^2\beta^3}{\sum_{t=1}^{4} \beta^{t-1}} - 1) \\ & + (T_{y,t+3} + T_{o,t+3})(\frac{R^2\beta^3 + R(1-\beta)}{\sum_{t=1}^{4} \beta^{t-1}} + R) + \frac{1 - \beta - R^2\beta^3}{R\sum_{t=1}^{4} \beta^{t-1}} T_{o,t+4} \\ & + (1 - \frac{R\beta^3 + \beta + 1}{R\sum_{t=1}^{4} \beta^{t-1}}) T_{o,t+5} \end{aligned} \tag{44}$$

$$\begin{aligned} S_{o,t+5} =& - \frac{R^4}{\sum_{t=1}^{4} \beta^{t-4}}(w_{m,t+2} - \rho R P_{t+1} H_{y,t+1}) - \frac{R^2}{\sum_{t=1}^{4} \beta^{t-4}}(R w_{m,t+3} + w_{m,t+4}) \\ & \frac{R^4}{\sum_{t=1}^{4} \beta^{t-4}}(T_{o,t+2} + T_{y,t+2}) + \frac{R^3}{\sum_{t=1}^{4} \beta^{t-4}}(T_{o,t+3} + T_{y,t+3}) \\ & - \frac{R^2}{\sum_{t=1}^{4} \beta^{t-4}} T_{o,t+4} + (1 - \frac{1}{\sum_{t=1}^{4} \beta^{t-4}} R T_{o,t+5}) \end{aligned} \tag{45}$$

Therefore, I summarize saving rates for different cohorts:

$$s_{y,t} = \frac{\beta + m}{1 + \beta + m} + \frac{1}{1 + \beta + m} \cdot \frac{w_{y,t+1} + T_{y,t+1}}{w_{y,t} + T_{y,t}} \tag{46}$$

$$s_{y,t+1} = \frac{(1-\rho)m - 1}{1 + \beta + m}(1 + \frac{T_{y,t+1}}{w_{y,t+1}}) - \frac{(2 + \beta + \beta m)R}{1 + \beta + m}(1 + \frac{T_{y,t}}{w_{y,t+1}}) \tag{47}$$

$$\begin{aligned} s_{m,t+2} =& \left(1 + \frac{1}{\sum_{t=1}^{4} \beta^{t-1}}\right) + \frac{1}{R^3 \sum_{t=1}^{4} \beta^{t-1}} \left[\frac{R^2 w_{m,t+3} + R w_{m,t+4} + R T_{o,t+4} + T_{o,t+5}}{w_{m,t+2} - T_{y,t+2} - T_{o,t+2}} \right] \\ & - \frac{1}{R^3 \sum_{t=1}^{4} \beta^{t-1}} \left[\frac{R^2(T_{y,t+3} + T_{o,t+3}) + \rho R^4 P_{t+1} H_{y,t+1}}{w_{y,t+2} - T_{y,t+2} - T_{o,t+2}} \right] \end{aligned} \tag{48}$$

$$\begin{aligned} s_{m,t+3} = &- RK_4 + K_3 \cdot \frac{w_{m,t+2} + \rho R P_{t+1} H_{y,t+1} - T_{o,t+2} - T_{y,t+2}}{w_{m,t+3} - T_{o,t+3} - T_{y,t+3}} \\ &- \frac{K_4}{R} \cdot \frac{R w_{m,t+4} + R T_{o,t+4} + T_{o,t+5}}{w_{m,t+3} - T_{o,t+3} - T_{y,t+3}} - \frac{T_{o,t+3} + T_{y,t+3}}{w_{m,t+3} - T_{o,t+3} - T_{y,t+3}} \end{aligned} \tag{49}$$

$$\begin{aligned} s_{o,t+4} = &R \frac{w_{m,t+2}}{w_{o,t+4} + T_{o,t+4}} \left(1 - \frac{1 + \beta R + R^2 \beta^3}{\sum_{t=1}^{4} \beta^{t-1}}\right) + \frac{\rho R^2 P_{t+1} H_{y,t+1}}{w_{o,t+4} + T_{o,t+4}} \left(\frac{R^2 \beta^3 - 1 + \beta R}{\sum_{t=1}^{4} \beta^{t-1}} + 1\right) \\ &- \frac{(R w_{m,t+3} + w_{o,t+4})}{w_{o,t+4} + T_{o,t+4}} \cdot \frac{R \beta^3 + \beta - 1}{\sum_{t=1}^{4} \beta^{t-1}} + \frac{(T_{o,t+2} + R T_{y,t+2})}{w_{o,t+4} + T_{o,t+4}} \left(\frac{1 - \beta R + R^2 \beta^3}{\sum_{t=1}^{4} \beta^{t-1}} - 1\right) \\ &+ \frac{(T_{y,t+3} + T_{o,t+3})}{w_{o,t+4} + T_{o,t+4}} \left(\frac{R^2 \beta^3 + R(1 - \beta)}{\sum_{t=1}^{4} \beta^{t-1}} + R\right) + \frac{1 - \beta - R^2 \beta^3}{R \sum_{t=1}^{4} \beta^{t-1}} \frac{T_{o,t+4}}{w_{o,t+4} + T_{o,t+4}} + \left(1 - \frac{R \beta^3 + \beta + 1}{R \sum_{t=1}^{4} \beta^{t-1}}\right) \frac{T_{o,t+5}}{w_{o,t+4} + T_{o,t}} \end{aligned} \tag{50}$$

$$\begin{aligned} s_{o,t+5} = &- \frac{R^4}{\sum_{t=1}^{4} \beta^{t-4}} \cdot \frac{w_{m,t+2} - \rho R P_{t+1} H_{y,t+1}}{T_{o,t+5}} - \frac{R^2}{\sum_{t=1}^{4} \beta^{t-4}} \cdot \frac{R w_{m,t+3} + w_{m,t+4}}{T_{o,t+5}} \\ &\frac{R^4}{\sum_{t=1}^{4} \beta^{t-4}} \frac{T_{o,t+2} + T_{y,t+2}}{T_{o,t+5}} + \frac{R^3}{\sum_{t=1}^{4} \beta^{t-4}} \frac{T_{o,t+3} + T_{y,t+3}}{T_{o,t+5}} \\ &- \frac{R^2}{\sum_{t=1}^{4} \beta^{t-4}} \frac{T_{o,t+4}}{T_{o,t+5}} + \left(1 - \frac{R}{\sum_{t=1}^{4} \beta^{t-4}}\right) \end{aligned} \tag{51}$$

.3.3 Proposition Proof

The six-period version of Proposition 1 also holds under certain condition in the six-period OLG model, which I call Proposition 2:

Proposition 2. *Saving rates of the middle-aged decreases with altruism and the tightness of borrowing constraint*[17]*:*

$$\frac{\partial s_{m,t+\tau}}{\partial \lambda} < 0, \frac{\partial s_{m,t+\tau}}{\partial \mu} < 0$$

$$\frac{\partial s_{m,t+\tau}}{\partial \rho} > 0, \frac{\partial s_{m,t+\tau}}{\partial \, P_{t+\tau}} > 0$$

for $\tau = 2, 3$.

Proof: The proof of $\frac{\partial s_{m,t+\tau}}{\partial \lambda} < 0$ and $\frac{\partial s_{m,t+\tau}}{\partial \mu} > 0$ are the similar with the proof of Proposition 1. Therefore, I only display the proof of $\frac{\partial s_{m,t+2}}{\partial \mu} < 0$ here. According to equation 37:

$$S_{m,t+2} = \left(1 + \frac{1}{\sum_{t=1}^{4} \beta^{t-1}}\right)(w_{m,t+2} - T_{y,t+2} + T_{o,t+2}) \\ + \frac{1}{R^3 \sum_{t=1}^{4} \beta^{t-1}} \left[R^2 w_{m,t+3} + R w_{m,t+4} + R T_{o,t+4} + T_{o,t+5} - R^2 (T_{y,t+3} + T_{o,t+3}) - \rho R^4 P_{t+1} H_{y,t+1}\right] \tag{52}$$

Let $x = T_{o,t+2} + T_{y,t+2}$, $y = T_{o,t+3} + T_{y,t+3}$, $z = RT_{y,t+2} + T_{y,t+3}$, *and* $w = RT_{o,t+2} + T_{o,t+3}$. Therefore, I can rearrange $S_{m,t+2}$:

$$\begin{aligned} S_{m,t+2} =& (1 + \frac{1}{\sum_{t=1}^{4} \beta^{t-1}})(w_{m,t+2} - x) + \frac{1}{R^3 \sum_{t=1}^{4} \beta^{t-1}}(-R^2 y) \\ &+ \frac{1}{R^3 \sum_{t=1}^{4} \beta^{t-1}}(R^2 w_{m,t+3} + R w_{m,t+4} + R T_{o,t+4} + T_{o,t+5} - \rho R^4 P_{t+1} H_{y,t+1}) \end{aligned} \tag{53}$$

So the partial differentiation is:

$$\begin{aligned} \frac{\partial S_{m,t+2}}{\partial \lambda} &= -\left[(1 + \frac{1}{\sum_{t=1}^{4}}) \cdot \frac{\partial x}{\partial \lambda} + \frac{1}{R \sum_{t=1}^{4}} \cdot \frac{\partial y}{\partial \lambda}\right] content... \\ &= -\frac{1}{R \sum_{t=1}^{4} \beta^{t-1}} \cdot \frac{\partial (Rx + y)}{\partial \lambda} \end{aligned} \tag{54}$$

[17] $1 - \mu$ refers to the tightness of borrowing constraint

From the Equation 35, I have:

$$c_{m,t+2} = C_1 - \theta_1(Rx + y) \tag{55}$$

where $C_1 = \dfrac{S_t}{R^3 \sum_{t=1}^{4} \beta^{t-1}}$, $\theta_1 = \dfrac{1}{R \sum_{t=1}^{4} \beta^{t-1}}$. From Equation 29, I have:

$$c_{y,t+2} = C_2 + \theta_2 z \tag{56}$$

where $C_2 = \dfrac{1}{R(1+\beta+m)}(Rw_{y,t} + W_{y,t+1})$, $\theta_2 = \dfrac{1}{R(1+\beta+m)}$.

From F.O.C. 26, I have $c_{m,t+2} = \dfrac{\beta^2}{\lambda} c_{y,t+2}$. We plug Equation 55 and Equation 56 in it, and I have:

$$C_1 - \theta_1(Rx + y) = \frac{\beta^2}{\lambda}(C_2 + \theta_2 z) \tag{57}$$

From the Equation 39, I have $c_{o,t+2} = C_3 + \theta_3[w - R^2(Rx + y)]$, where $C_3 = \dfrac{1}{R \sum_{t=1}^{4} \beta^{t-3}}(R^3 w_{m,t} - \rho R^4 P_{t-1} H_{y,t-1} + R^2 w_{m,t+1} + R w_{m,t+2})$, $\theta_3 = \dfrac{1}{R \sum_{t=1}^{4} \beta^{t-3}}$. Together with F.O.C. 27, I have:

$$C_1 - \theta_1(Rx + y) = \frac{1}{R^2 \mu}[C_3 + \theta_3(w - R^2(Rx + y))] \tag{58}$$

Also, I have that $Rx + y = z + w$. Let

$$Rx + y = u, \tag{59}$$

then I end up with the equations:

$$C_1 - \theta_1 \cdot u = \frac{\beta^2}{\lambda}(C_2 + \theta_2 z) \tag{60}$$

$$C_1 - \theta_1 \cdot u = \frac{1}{\beta^2 \mu}[C_3 + \theta_3(w - R^2 u)] \tag{61}$$

$$z + w = u \tag{62}$$

Therefore, I end up with

$$u = \frac{\dfrac{C_1 \lambda / \beta^2 - C_2}{\theta_2} + \dfrac{C_1 \mu \beta^2 - C_3}{\theta_3}}{1 + \dfrac{\lambda(1+\beta+m)}{\sum_{t=1} 4\beta^{t+1}} + \dfrac{\mu}{R} - R^2}. \tag{63}$$

Plug this into Equation 54, I have:

$$\begin{aligned}\frac{\partial s_{m,t+2}}{\partial \lambda} &= -\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}}\cdot\frac{\partial u}{\partial \lambda}\\ &= -\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}}\cdot\frac{C_1(\frac{1+\mu/R-R^2}{\theta_2\beta^2}-\frac{1+\beta+m}{\sum_{t=1}^{4}\beta^{t+1}}\cdot\frac{\mu\beta^2}{\theta_3})+\frac{1+\beta+m}{\theta_3\sum_{t=1}^{4}\beta^{t+1}}\cdot C_3}{[1+\frac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}}+\frac{\mu}{R}-R^2]^2}\end{aligned}\tag{64}$$

In the formula below, $\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}}>0$, $C_1>0, C_3>0$, so the sign of $\frac{\partial S_{m,t+2}}{\partial \lambda}$ depends on the sign of $\frac{1+\mu/R-R^2}{\theta_2\beta^2}-\frac{1+\beta+m}{\sum_{t=1}^{4}\beta^{t+1}}\cdot\frac{\mu\beta^2}{\theta_3}$.

$$\begin{aligned}\frac{1+\mu/R-R^2}{\theta_2\beta^2}-\frac{1+\beta+m}{\sum_{t=1}^{4}\beta^{t+1}}\cdot\frac{\mu\beta^2}{\theta_3} &= \frac{(1+\frac{\mu}{R}-R^2)\sum_{t=1}^{4}\beta^{t+1}\cdot\theta_3-(1+\beta+m)\mu\beta^4\theta_2}{\theta_2\theta_3\sum_{t=1}^{4}\beta^{t+3}}\\ &= \frac{\frac{\beta^4}{R}(1-R^2)+\frac{\beta^4\mu}{R^2}(1-R)}{\theta_2\theta_3\sum_{t=1}^{4}\beta^{t+3}}\end{aligned}\tag{65}$$

If $\mu<\frac{R(R-1)}{R^2}$, then I have $\frac{1+\mu/R-R^2}{\theta_2\beta^2}-\frac{1+\beta+m}{\sum_{t=1}^{4}\beta^{t+1}}\cdot\frac{\mu\beta^2}{\theta_3}>0$. Therefore, I conclude that: If $\mu<\frac{R(R-1)}{R^2}$, then $\frac{\partial S_{m,t+2}}{\partial \lambda}<0$.

Next, I calculate $\frac{\partial S_{m,t+2}}{\partial \mu}$.

$$\begin{aligned}\frac{\partial S_{m,t+2}}{\partial \mu} &= -\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}}\cdot\frac{\partial u}{\partial \mu}\\ &= -\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}}\cdot\frac{C_1R(R^2-1)\sum_{t=1}^{4}\beta^{t-1}+\frac{C_2}{\theta_2}+\frac{C_3}{\theta_3}}{[1+\frac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}}+\frac{\mu}{R}-R^2]^2}<0\end{aligned}\tag{66}$$

Next, I prove for $\dfrac{\partial S_{m,t+2}}{\partial \rho}$.

$$\begin{aligned}
\frac{\partial S_{m,t+2}}{\partial \rho} &= -\frac{1}{R\sum_{t=1}^{4}\beta^{t-1}} \cdot \frac{\partial u}{\partial \rho} \\
&= \frac{\left(\dfrac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}} - \mu + R^2\right) R^2 P_{t+1} H_{y,t+1}}{R\sum_{t=1}^{4}\beta^{t-1}\left(1 + \dfrac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}} + \dfrac{\mu}{R} - R^2\right)}
\end{aligned} \tag{67}$$

Since $R > 1$, $\mu < 1$, I have $\dfrac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}} - \mu + R^2 > 0$. Therefore, the sign of $\dfrac{\partial S_{m,t+2}}{\partial \rho}$ depend on the sign of $1 + \dfrac{\lambda(1+\beta+m)}{\sum_{t=1}^{4}\beta^{t+1}} + \dfrac{\mu}{R} - R^2$. If $\alpha_1 \cdot \lambda + \alpha_2 \cdot \mu > R^2 - 1$, $\dfrac{\partial S_{m,t+2}}{\partial \rho} > 0$, where $\alpha_1 = \dfrac{1+\beta+m}{\sum_{t=1}^{4}\beta^{t+1}}$, and $\alpha_2 = 1/R$.

Next, I prove that $\dfrac{s_{m,t+\tau}}{P_{t+\tau}} < 0$ while taking $\tau = 3$. Therefore, $s_{m,t+3}$ is the saving rate of parents in his second period of middle age, and P_{t+3} is price of the house bought by his children. The intuition is that higher prices of children's houses lead to larger transfers given by their parents. Larger transfers leads to drop of saving rates.

According to Equation 37, we know:

$$\begin{aligned}
\frac{\partial s_{m,t+2}}{\partial (P_{t+3}H_{y,t+3})} &= -\left(1 + \frac{1}{\sum_{t=1}^{4}\beta_1^{t-1}}\right) \cdot \frac{\partial T_{y,t+2}}{\partial (P_{t+3}H_{y,t+3})} - \frac{1}{R\sum_{t=1}^{4}\beta^{t-1}} \cdot \frac{\partial T_{y,t+3}}{\partial (P_{t+3}H_{y,t+3})} \\
&= -\frac{1}{\sum_{t=1}^{4}\beta_1^{t-1}} \cdot \frac{\partial (RT_{y,t+2} + T_{y,t+3})}{\partial (P_{t+3}H_{y,t+3})} - \frac{\partial T_{y,t+2}}{\partial (P_{t+3}H_{y,t+3})}
\end{aligned} \tag{68}$$

According to Equation 33,

$$\frac{\partial (RT_{y,t+2} + T_{y,t+3})}{(P_{t+3}H_{y,t+3})} = \frac{1+\beta+m}{\beta m} > 0$$

From Equation 77, we know that:

$$\frac{\partial T_{y,t+2}}{\partial (P_{t+3}H_{y,t+3})} > 0$$

Therefore, we have $\dfrac{\partial s_{m,t+2}}{\partial (P_{t+3}H_{y,t+3})} < 0$. Since $H_{y,t+3} > 0$, we have $\dfrac{\partial s_{m,t+2}}{\partial P_{t+3}} < 0$ The proof for $\dfrac{\partial s_{m,t+3}}{\partial P_{t+3})} < 0$ is similar. $\mathcal{Q.E.D}$.

.4 Technical Details for Estimations

.4.1 Intergenerational Transfer and Life-Cycle Saving Rates

According to Formulas 46 to 51, I summarize saving rates for all age cohorts:

$$s_{y,t} = F_1(T_{y,t}, T_{y,t+1}) \tag{69}$$

$$s_{y,t+1} = F_2(T_{y,t}, T_{y,t+1}) \tag{70}$$

$$s_{m,t+2} = F_3(T_{y,t}, T_{y,t+1}, T_{y,t+2} + T_{o,t+2}, T_{y,t+3} + T_{o,t+3}) \tag{71}$$

$$s_{m,t+3} = F_4(T_{y,t}, T_{y,t+1}, T_{y,t+2} + T_{o,t+2}, T_{y,t+3} + T_{o,t+3}, RT_{o,t+4} + T_{o,t+5}) \tag{72}$$

$$s_{o,t+4} = F_5(T_{y,t}, T_{y,t+1}, T_{y,t+2} + T_{o,t+2}, T_{y,t+3} + T_{o,t+3}, T_{o,t+4}, T_{o,t+5}) \tag{73}$$

$$s_{o,t+5} = F_6(T_{y,t}, T_{y,t+1}, T_{y,t+2} + T_{o,t+2}, T_{y,t+3} + T_{o,t+3}, T_{o,t+4}, T_{o,t+5}) \tag{74}$$

In each equation, the black terms can be observed from the data and the red terms need to be estimated. That is to say, to estimate saving rates, I need to estimate **future transfers**. In order to estimate life-cycle transfers, I need to estimate $T_{y,t+1}$, $T_{y,t+3} + T_{o,t+3}$, $RT_{o,t+4} + T_{o,t+5}$ and $T_{o,t+5}$. Combining budget constraint and the first order condition of housing. Budget constraint yields to:

$$T_{y,t+1} = \beta R c_{y,t} + (1-\rho) P_{t+1} H_{y,t+1} - w_{y,t+1} - R a_{y,t} \tag{75}$$

And the F.O.C. 21 yields to:

$$P_{t+1} H_{y,t+1} = \frac{\beta R m}{(1+\beta+m)}(w_{y,t} + T_{y,t}) + \frac{\beta m}{1+\beta+m}(w_{y,t+1} + T_{y,t+1}) \tag{76}$$

These two equations lead to:

$$\begin{aligned} T_{y,t+1} = {} & \frac{(1+\beta+R)\beta R}{1+\beta(1-m)+m} \cdot c_{y,t} + \frac{(1-\rho)\beta R m}{1+\beta(1-m)+m}(w_{y,t} + T_{y,t}) \\ & + \frac{(1-\rho)\beta m}{1+\beta(1-m)+m} \cdot w_{y,t+1} \end{aligned} \tag{77}$$

Then I estimate $T_{y,t+3} + T_{o,t+3}$. This can be done by combining Equation 59 and Equation 63.

Therefore, I have

$$
\begin{aligned}
T_{y,t+3} + T_{o,t+3} &= u - Rx \\
&= \frac{\dfrac{C_1\lambda/\beta^2 - C_2}{\theta_2} + \dfrac{C_1\mu\beta^2 - C_3}{\theta_3}}{1 + \dfrac{\lambda(1+\beta+m)}{\sum_{t=1} 4\beta^{t+1}} + \dfrac{\mu}{R} - R^2} - R(T_{y,t+2} + T_{o,t+2})
\end{aligned} \tag{78}
$$

$RT_{o,t+4} + T_{o,t+5}$ can be estimated from 35:

$$
c_{m,t+2} = \frac{1}{R^3 \cdot \sum_{t=1}^4 \beta^{t-1}} \cdot \left[S_t - R^2(T_{y,t+3} + RT_{y,t+2}) - R^2(T_{o,t+3} + RT_{o,t+2})\right]
$$

where $S_t = R^3 w_{m,t+2} + R^4 a_{y,t+1} + R^2 w_{m,t+3} + R w_{m,t+4} + RT_{o,t+4} + T_{o,t+5}$. We can observe $c_{m,t+2}$, $T_{i,t+2}$, $T_{i,t+3}$ from the data, where $i = 2, 3$. And $RT_{o,t+4} + T_{o,t+5}$ can be back out from term S_t. Therefore, I have:

$$
\begin{aligned}
RT_{o,t+4} + T_{o,t+5} =& c_{m,t+2} \cdot \frac{1}{R^3 \cdot \sum_{t=1}^4 \beta^{t-1}} + R^2(T_{y,t+3} + RT_{y,t+2}) + R^2(T_{o,t+3} + RT_{o,t+2}) \\
& - R^3 w_{m,t+2} - R^4 a_{y,t+1} - R^2 w_{m,t+3} - R w_{m,t+4}
\end{aligned} \tag{79}
$$

$T_{o,t+5}$. can be estimated from Equation above with the observation of $T_{o,t+4}$:

$$
\begin{aligned}
T_{o,t+5} =& c_{m,t+2} \cdot \frac{1}{R^3 \cdot \sum_{t=1}^4 \beta^{t-1}} + R^2(T_{y,t+3} + RT_{y,t+2}) + R^2(T_{o,t+3} + RT_{o,t+2}) \\
& - R^3 w_{m,t+2} - R^4 a_{y,t+1} - R^2 w_{m,t+3} - R w_{m,t+4} - RT_{o,t+4}
\end{aligned} \tag{80}
$$

Following Equation 77 to Equation 80, I generate the estimation of intergenerational transfer in Figure 27. (This is the same as Figure 1.9.) Furthermore, I plug the estimated transfers into Equation 69 - Equation 74, I end up with the estimation of life-cycle saving rates in Figure 1.10. (This is the same as Figure 1.10.) One thing I would like to point out is how the middle-aged households allocate $T_{y,t}$ and $T_{y,t+1}$. The allocation does not affect housing value which their children choose. Housing value only depends on the inter-temporal transfer $RT_{y,t} + T_{y,t+1}$. Allocation only affect their consumption in different periods.

.4.2 Estimation of Life-Cycle Saving Rates: Two Groups

In this section, the calibrated parameters for two groups are displayed. Group one is made up of households who generate intergenerational transfers, while group two is made up of households who do not generate intergenerational transfers. The method is the same with that used to calibrate

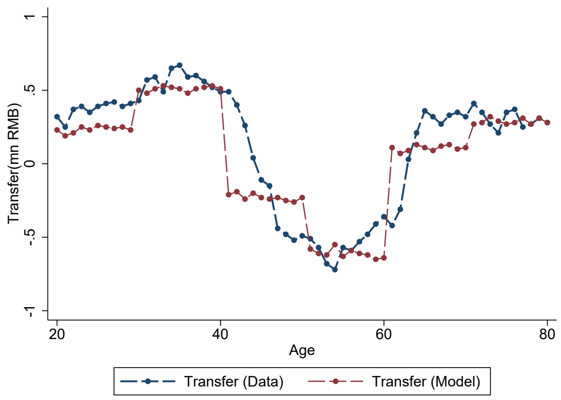


Figure 27: Intergenerational Transfer: data and estimation

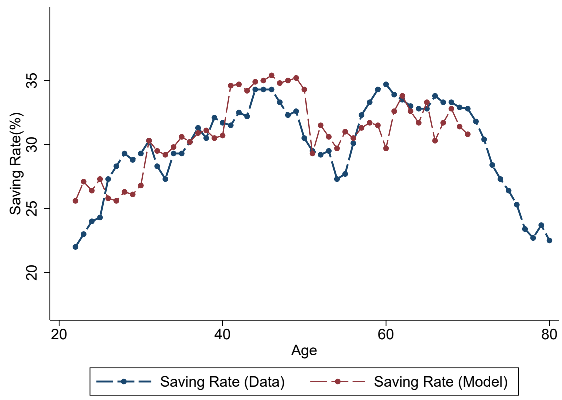


Figure 28: Life-Cycle Saving Rates: data and estimation

Data source: China Household Finance Survey

parameters in Table 21 and 1.3.

Table 21: Calibration of Model Parameters: Two Groups

Par.		Transfer	No-transfer	Target
β	discount rate	0.9	0.9	borrowed from literature
κ	utility weight on house	0.28	0.29	F.O.C. of housing
R	interest rate	1.0515	1.05	Long-term interest rate
ρ	credit constraint	0.719	0.741	Mortgage loan
λ	altruism on children	0.734	0	F.O.Cs of transfer
μ	altruism on parents	0.247	0	F.O.Cs of transfer
λ	growth rate of income	0.032	0.029	CHFS data

.4.3 Estimation of US Life-Cycle Saving Rates

Apart from simulating the saving rates of Chinese households, I simulate the age-saving profile for US households, using the Survey of Consumer Finance (SCF, 2013). The main purpose of this exercise is to show that our model is not limited to the scenario of Chinese households. It is able to explain saving behavior of households in other countries, for instance, the United States. The key factors which lead to different behaviors are model intuitions hidden behind the parameters.

We follow the method used to estimate life-cycle saving rates of China. Here, I first estimate two groups of model parameters. Group 1 consists of parameters which are easily estimated from data or borrowed from other studies. Group 2 consists of parameters which are estimated using GMM.

Group 1 includes discount rate β, interest rate R, annual income growth rate λ and credit constraint parameter ρ. The values of parameters are displayed in Table 22. Discount rate β is borrowed from other studies. Interest rate takes the average value of Federal Funds Rate (FFR) in the year

Table 22: Calibration of Model Parameters: Group 1

Parameter		Value	Target
β	Discount Rate	0.90	Borrowed from Other Studies
R	Interest Rate	1.13	Federal Funds Rate (FFR)
ρ	Credit Constraint	0.82	Mortgage Loan
λ	Annual Growth Rate of Income	3.71%	SCF Income Data

2013. The value of credit constraint parameter ρ is 0.815, higher than its counterpart in China. This implies that the financial market in US allows households to borrow more as a fraction of their housing value. The value of annual growth rate of income λ in US is lower than that of China, by around 2.5%. This result is consistent with the data from macro studies. Gross National Income (GNI) Per Capita implies a gap of 2.71% between China and US.

Then, I estimate the utility weight on housing κ, altruism parameter towards children λ, and altruism parameter towards parents μ using the GMM method explained in Section 1.4.1. The three moment conditions are the same which are summarized in $h(\gamma, \zeta, \boldsymbol{X})$. The only difference is the empirical counterpart of $h(\gamma, \zeta, \boldsymbol{X})$: $g(\gamma, \zeta, \boldsymbol{X}) = \frac{1}{N} \sum_{i=1}^{N} h(\gamma, \zeta, \boldsymbol{X_i})$. Because I use different data sets here.

The results are displayed in Table 23. Compared to the parameters of Chinese households (Table 1.3), US households display less altruism to their children while same level of altruism to their parents. Here I point out that altruism in this paper is not equal to altruism in a broad sense. Therefore, it is unfair to make the statement from the values of λ that US parents in general care less about their children than Chinese parents. A proper way to understand the different values of λ should be the following. The altruism of parents which is related with housing of their children differs across countries. In US, this altruism is less than that of China. And Altruism of parents μ are similar in US and China.

Table 23: *Group 2 Parameters: GMM Estimation*

Parameter		Two-Step
κ	utility weight on housing	0.173**
		(0.073)
λ	altruism on children	0.437**
		(0.021)
μ	altruism on parents	0.209***
		(0.071)

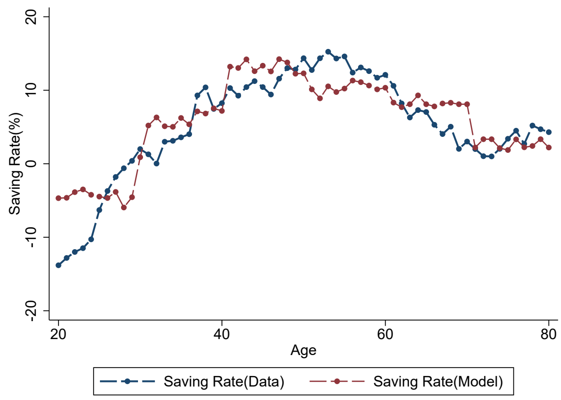


Figure 29: US Age-saving Profile, 2013
Data source: China Family Panel Studies

Using the parameters calibrated in Table 22 and Table 23, I estimate the life-cycle saving rates of US households. The results are displayed in Figure 29. In the survey data, US households display the traditional hump-shaped saving curve. And average saving rates of households is 5.78%. The model estimation gives close result to the data. The estimated life-cycle saving rates of US households form a hump-shaped pattern. And the estimated average saving rate is 6.17%.

Comparing the estimated life-cycle saving rates of Chinese households and US households, I have three observations. We first describe the observations, and then explain how different parameter values ρ, λ and μ altogether give rise to them. First, average saving rate of US households is much lower than that of Chinese households by around 23%. Second, young households (with age 20-30) in US have negative saving rates, while the young households in China have positive saving rates. Finally, the age-saving profile of US households is hump-shaped while that of Chinese households is "camel-shaped".

Comparing the data and the model estimation, I have two implications. First, our model is not constrained to the scenario of China, and displays generality in explaining saving patterns elsewhere. Second, the strength of the two mechanisms (*"saving-altruism"* and *"saving-credit constraint"*)are robust enough to not only raise the saving rates of the middle-aged households, but also changes it from a local minimal point of the curve (China scenario) to a local maximal point (US scenario).

.5 Robustness Check

.5.1 Estimation of Model Parameters: Least Squares

In this section, I display another method to calibrate parameters κ, ρ, λ and μ. They are calibrated/estimated targeting on some moments of the model, using CHFS data.

Credit constraint parameter ρ. ρ is the fraction that young households could borrow against the value of their houses. We therefore estimate ρ according to the binding credit constraint and data of mortgage loan. Credit constraint condition yields that:

$$a_{y,t+1} = -\rho P_{t+1} H_{y,t+1} \tag{81}$$

In our data, $a_{y,t+1}$ is observable from the mortgage loan contract for each household, $P_{t+1}H_{y,t+1}$ can be observed from the data. Therefore, I run the OLS regression:

$$a_{y,t+1} = c + \rho \cdot P_{t+1} H_{y,t+1} + u \tag{82}$$

And estimate $\hat{\rho}$ should be our estimated credit constraint parameter.

Housing weight parameter κ. κ can be estimated using the F.O.C. condition of housing value Equation 21:

$$H_{y,t+1} : P_{t+1} H_{y,t+1} = \frac{\kappa \sum_{t=1}^{6} \beta^{t-1}}{1-\rho} \cdot c_{y,t+1}$$

Taking log forms for both sides yields that:

$$log(P_{t+1} H_{y,t+1}) = log(\frac{\kappa \sum_{t=1}^{6} \hat{\beta}^{t-1}}{1-\hat{\rho}}) + log(c_{y,t+1}) \tag{83}$$

The terms $log(P_{t+1}H_{y,t+1})$ and $c_{y,t+1}$ can be observed from the data. $\hat{\beta}$ and $\hat{\rho}$ have already been estimated or calibrated. Therefore, I run the regression:

$$log(P_{t+1} H_{y,t+1}) = \psi_1 + \alpha \cdot log(c_{y,t+1}) + u \tag{84}$$

Estimate $\hat{\psi}_1$ should be equal to $\frac{\hat{\kappa} \sum_{t=1}^{6} \hat{\beta}^{t-1}}{1-\hat{\rho}}$. Then I back out $\hat{\kappa}$ from this formula:

$$\hat{\kappa} = \frac{e^{\hat{\psi}_1}(1-\hat{\rho})}{\sum_{t=1}^{6} \hat{\beta}^{t-1}} \tag{85}$$

Altruism parameter λ. Altruism parameter towards children λ can be estimated targeting on the F.O.C. of transfers to children, Equation 26:

$$c_{m,t+2} = \frac{\beta^2}{\lambda} c_{y,t+2}$$

The terms $c_{m,t+2}$ and $C_{y,t+2}$ can be observed from the data. $\hat{beta}$ has been estimated. Therefore, I run the OLS regression:

$$c_{m,t+2} = c + \psi_2 \cdot c_{y,t+2} + u \tag{86}$$

Estimates $\hat{\psi}_2$ should be equal to $\frac{\hat{\beta}^2}{\hat{\lambda}}$. Then I back out λ from this formula:

$$\hat{\lambda} = \frac{\hat{\beta}^2}{\psi_2} \tag{87}$$

Altruism parameter μ. The altruism parameter towards parents μ can be estimated from the F.O.C. of transfer to the elderly, Equation 27:

$$c_{m,t+2} = \frac{1}{\mu\beta^2} c_{o,t+2}$$

Therefore, I run the OLS regression:

$$c_{m,t+2} = c + \psi_3 \cdot c_{o,t+2} + u \tag{88}$$

Estimate $\hat{\psi}_3$ should be equal to $\frac{1}{\hat{\mu}\hat{\beta}^2}$. Then I back out $\hat{\mu}$ from the formula:

$$\hat{\mu} = \frac{1}{\hat{\psi}_3\hat{\beta}^2} \tag{89}$$

The results of regressions 82, 85, 87 and 89 are displayed in Table .

Table 24: Calibration of parameters targeted on moments

Regressions	Equation 82 $\hat{\rho}$	Equation 85 $\hat{\psi}_1$	Equation 87 $\hat{\psi}_2$	Equation 89 $\hat{\psi}_3$
Estimates	0.734***	5.108***	1.096**	4.861***
	(0.213)	(2.137)	(0.412)	(2.319)
R-square	0.193	0.214	0.191	0.187

.5.2 Effects of Altruism: Natural Experiment of Loss of Children

In this section, I launch the same regression on various treatment groups and control groups as a robustness check. In Section 2.3, the treatment group is composed of households who accidentally lost their children and have no children up to the survey year; while the control group is composed of households who have children. In this section, we launch the following robustness check, summarized in Table 25.

Table 25: Treatment Groups and Control Groups

	Treatment Group	Control Group
Category 1	Parents: $Chd > 0$	Parents: $Accd\&Chd = 0$
Category 2	Parents: $Chd > 0$	Parents: $Chd = 0$
Category 3	Parents: $Accd\&Chd > 0$	Parents: $Accd\&Chd = 0$
Category 4	Parents: $Accd\&Chd > 0$	Parents: $Chd = 0$

Accd refers to parents have accidentally lost their children. Therefore, control group in Category 1 refers to parents who lost their chidlren out of accidents and do not have any more children up to the survey year. Category 1 is the main regression in Section 2.3. Control group in Category 2 refers to parents who have no children up to the survey year, either because of accidents, or out of their own decisions. Treatment group of Category 3 refers to parents who accidentally lost their children but have birth up to the survey year, either by giving birth, or by adoption. In Table 26 and 27, I display the balancing table for different groups of households. Each category summarizes the significant difference with the p-statistics below. Years of educatioin, rural/urban, health condition and annual income are significantly different between treatment group and control group. Parents with higher education, better health condition, higher annual income and live in urban area tend to have children, and have lower probability of accidental shock than their counterparts. In the regressions below, we control all these variables.

Table 28 display the regressions under four categories displayed above. The results do not change much, from Column (1) to Column (4). One thing to note is that saving rate difference is smaller in Category 2 and Category 4 (10.3% and 10.4%), compared with Category 1 and Cateory 3 (11.7% and 11.6%). Also, the same pattern shows for income. This confirms the concern that people do not give birth to children for endogenous reasons, such as income.

Table 26: Balancing Table for Different Groups of Households

	Prts: $Chd > 0$	Prts: $Accd\&Chd = 0$	Prts: $Chd = 0$	Category 1	Category 2
	(1)	(2)	(3)	(4)	(5)
Percentage	90.12%	6.32%	9.88%	83.8%	80.24%
Avg. Age	53.46	52.53	53.08	0.93	0.38
				(0.07)	(0.08)
Yeas of Edu.	11.91	10.38	9.03	1.53*	2.88***
				(2.03)	(3.12)
Rural/Urban	0.37	0.43	0.31	-0.06*	0.06
(Rural=1)				(-1.97)	(1.21)
Health Condition	0.21	0.17	0.22	0.04**	-0.01
(Healthy=1)				(2.14)	(0.73)
Annual Income	8891.23	8712.34	8012.31	178.89	878.02**
(*RMB*)				(1.52)	(4.45)
Saving Rates	23.67%	34.54%	29.12%	-10.57%***	-5.45% **
				(9.19)	(2.78)

Note: Category 1 refers to Column (1)-(2), and Category 2 refers to Column (1)-(3). In the brackets are t-statistics for test in which the null hypothesis is that the difference is zero. "Healthy" is defined as households do not have any chronic disease, genetic disease, and their current physical examination reports no diseases. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 27: Balancing Table for Different Groups of Households

	Prts: $Accd\&Chd > 0$	Prts: $Accd\&Chd = 0$	Prts: $Chd = 0$	Category 3	Category 4
	(1)	(2)	(3)	(4)	(5)
Percentage	8.21%	6.32%	9.88%	2.89%	-1.67%
Avg. Age	54.17	52.53	53.08	1.64	1.09
				(0.11)	(0.21)
Avg. Age_Accd	31.71	45.81	NA	-14.1***	
				(6.12)	
Yeas of Edu.	10.91	10.38	9.03	0.53	1.88*
				(1.32)	(2.12)
Rural/Urban	0.42	0.43	0.31	-0.01	0.11*
(Rural=1)				(0.34)	(1.91)
Health Condition	0.18	0.17	0.22	0.01	-0.04*
(Healthy=1)				(0.14)	(2.03)
Annual Income	8763.12	8712.34	8012.31	50.78	750.81**
(*RMB*)				(1.33)	(3.77)
Saving Rates	24.13%	34.54%	29.12%	-10.41%***	-4.99% **
				(8.59)	(2.21)

Note: Category 3 refers to Column (1)-(2), and Category 4 refers to Column (1)-(3). In the brackets are t-statistics for test in which the null hypothesis is that the difference is zero. "Healthy" is defined as households do not have any chronic disease, genetic disease, and their current physical examination reports no diseases. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 28: Effects of Altruism: Robustness Check with Category 1-4

Dependent Variable: Saving Rates of Parents				
	Category 1	Category 2	Category 3	Category 4
$\mathbb{1}_{treat}$	0.117***	0.103***	0.116***	0.104***
	(0.031)	(0.033)	(0.032)	(0.034)
$\mathbb{1}_{treat} \times Age^2$	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Age^2_{Prt}	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Age_{Prt}	-0.043**	-0.042**	-0.042***	-0.042***
	(0.022)	(0.020)	(0.021)	(0.020)
$Log(Income^{Prt})$	0.037***	0.033***	0.036***	0.033**
	(0.018)	(0.016)	(0.017)	(0.016)
Number of Children	-0.041**	-0.042**	-0.041**	-0.042**
	(0.022)	(0.021)	(0.020)	(0.020)
City FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Year × City	YES	YES	YES	YES
Year × Industry	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES
R-squared	0.179	0.175	0.181	0.180
Sample size	6,625	6,625	6,625	6,625

Note: Data source: CFPS (2010, 2012, 2014). Sample restricted to parents whose ages fall between 40-60 and where the parent-children pair information is complete. Categories are defined in Table 25. Other controls include: gender of households head, ethnic group, "Hukou", education level, marriage status, health condition, ages, occupation, whether working in state owned-enterprise (SOE), whether retired (only for parents), whether they participate in social security plans. Robust standard errors are in the parentheses. *** stands for $p < 0.01$, ** stands for $p < 0.05$, * stands for $p < 0.1$.

.6 Migration between Different Tiers of Cities

In this section, I investigate the cities in which children settle down when they leave their parents. And what influences their choices of cities? Table 29 shows the distribution of children's cities. For parents living in either first tier or second tier cities, more than 80% of their children still live in Tier I and Tier II cites. Only less than 20% move to third tier cities. Therefore, migration from the first two tiers to the third tier is scarce. For parents living in third tiers, more than half of their children stay in the same tier with them, less than half move to more expensive cities. To sum up this figure, if parents live in more expensive cities, their children have higher probability of living in expensive cities.

Then, in table 29, I display features of households living in different cities. Parents living in more expensive cities bear less children. And less of them share houses with their children. Also, they have higher income, make more transfers, and have lower saving rates. Figure 2.8 display how housing prices in children's cities change with average income of their parents. There is a positive relationship between housing prices and incomes. If high income parents tend to have high saving rates. This would leads to a downward bias of our estimation.

Table 29: Features about Parents and Children living in Different Cities

	Parents' Location			
	Tier I	Tier II	Tier III	Average
Number of Children	1.21	1.37	1.51	1.41
Co-residence	7.35%	8.75%	12.41%	10.13%
Annual Income of Parents (1,000 RMB)	73.5	59.4	35.6	42.9
Annual Income of Children (1,000 RMB)	62.7	53.7	37.7	40.3
Transfer on Housing	29.7	26.7	13.8	17.5
Saving Rates of Parents	27.3%	25.6%	33.7%	30.3%
	Children's Location			
	Tier I	Tier II	Tier III	Average
Number of Children	1.43	1.39	1.42	1.41
Co-residence	8.31%	8.54%	10.12%	9.74%
Annual Income of Parents (1,000 RMB)	50.3	51.2	35.9	41.5
Annual Income of Children (1,000 RMB)	47.5	47.3	33.1	37.8
Transfer on Housing	21.5	17.8	11.5	13.7
Saving Rates of Parents	29.9%	28.3%	31.3%	30.1%

Note: Data source is CFPS (2010, 2012).

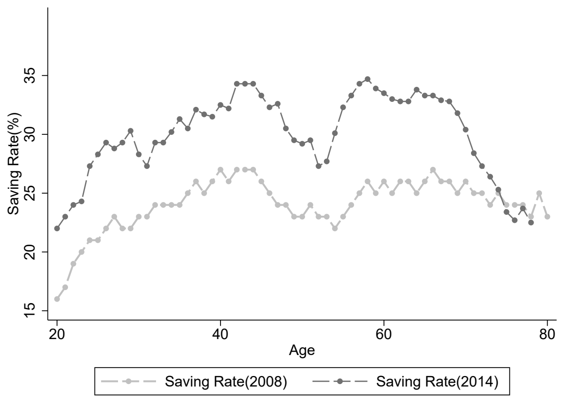


Figure 30: Age-Saving Profile of Chinese Households 2008, 2014

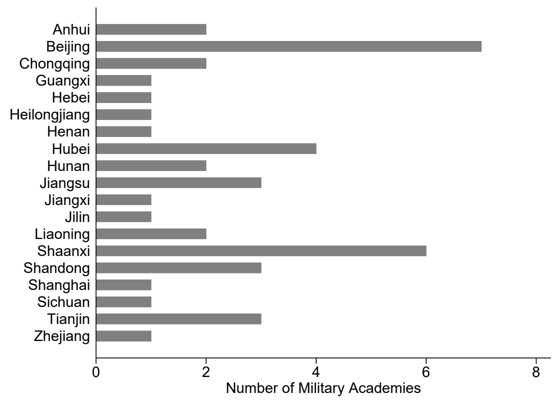
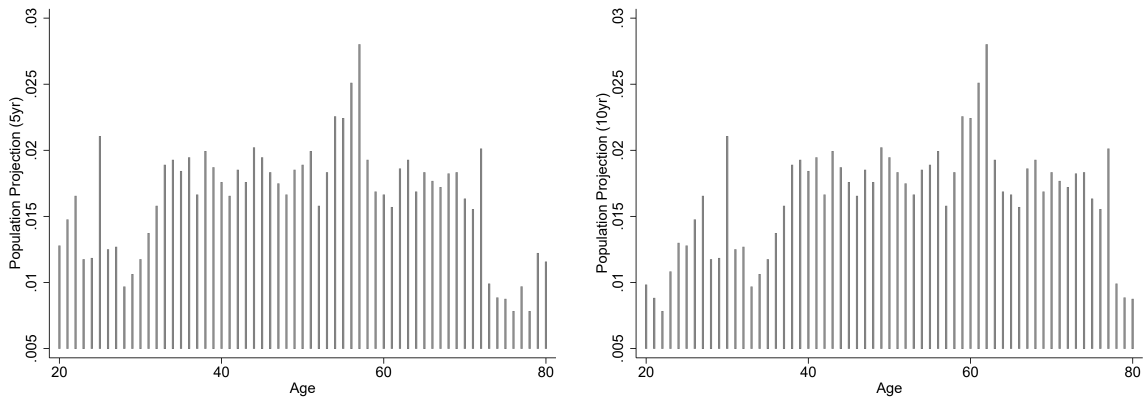


Figure 31: Distribution of Military Academies Across Provinces

Data source: China Household Finance Survey



Notes: Data source: China Household Finance Survey.

Figure 32: Population Projection: 3-year forecast and 10-yr forecast

.7 Additional Tables and Figures

.8 Data Description

.8.1 Capital IQ

The firms are seminated among 8 main sectors: energy, materials, industries, consumer discretionary, consumer staples, health care, information technology and utilities, according to the classification of S&P.[18]

The available information of each firm can be summarized into three categories: general information, balance sheet information and business relationship information.

[18] The 8 sectors are further fined to 159 smaller sectors. The detail can be seen in the Data Appendix.

General information:

The country in which the firm operates;

The country in which its headquarter locates;

The age of the firm;

Total employment;

The exchange on which it is listed;

Company type;

Company status;

Ownership structure.

Balance sheet information:

Balance sheet information is available in each month for the past 5 years.

Market value of the firm (in $mm);

Total revenue;

EBIT;

Asset debts structure.

Business relationship:

It provides the information of supplier-customer, licensee-licensor and strategic alliance connections. This information is collected by S&P Capital IQ from the firm's annual report submitted to Securities and Exchange Commission. [19]. For each firm, we are able to observe:

The identity of its trading partners.

For instance, IBM has 200 *suppliers, among which there are Apple Inc., AcBel Polytech Inc., Beijing Camelot Technology Co., Ltd. and so on. And it has* 344 *customers, among which there are Apple Inc., Australian Broadcasting Inc., Bank of China Ltd., and so on.*

The year in which this relationship is built. However, the volume of each transaction is beyond reach.

[19]In United States, it is the $10 - K$ form

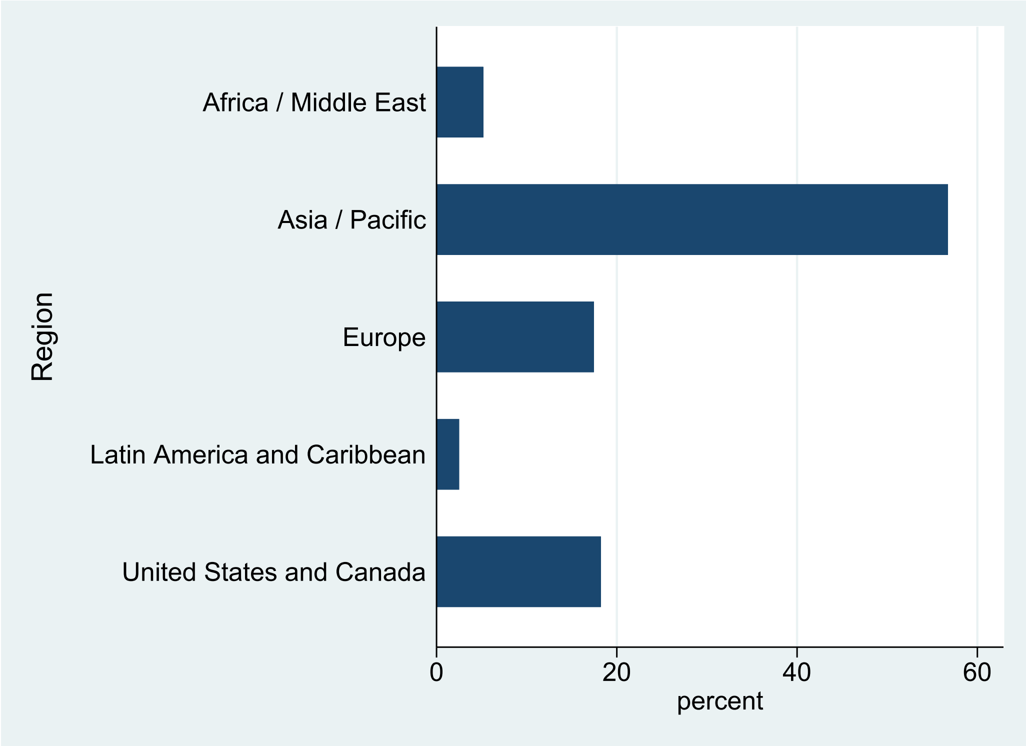
.8.2 Firm Characteristics

In this section, we present some general characteristics of the firms in our data set. These include: geographic distribution, sector distribution, summary statistics of the firms' age, latest annual revenue (calendar year), profit, employment and total enterprise value (TEV).

Figure 33 presents the percentage of firms in each of the five regions: Africa/Middle East, Asia/Pacific, Europe, Latin America and Caribbean, United States and Canada. Asia/Pacific takes up more than half of the amount, with the United States and Canada being the second. Europe, the third, has considerable number of firms compared to the United States and Canada. Latin America/Caribbean and Africa/Middle East have very small number of firms in this sample. Moreover, we also display the geographic distribution of firms in terms of their revenues in Figure 34. By comparing the two figures, we can observe that the percentages of Europe and the United States/Canada significantly increase when we change from numbers to revenues. This implies that the firms in Europe and the US/Canada sell more than the firms in China.

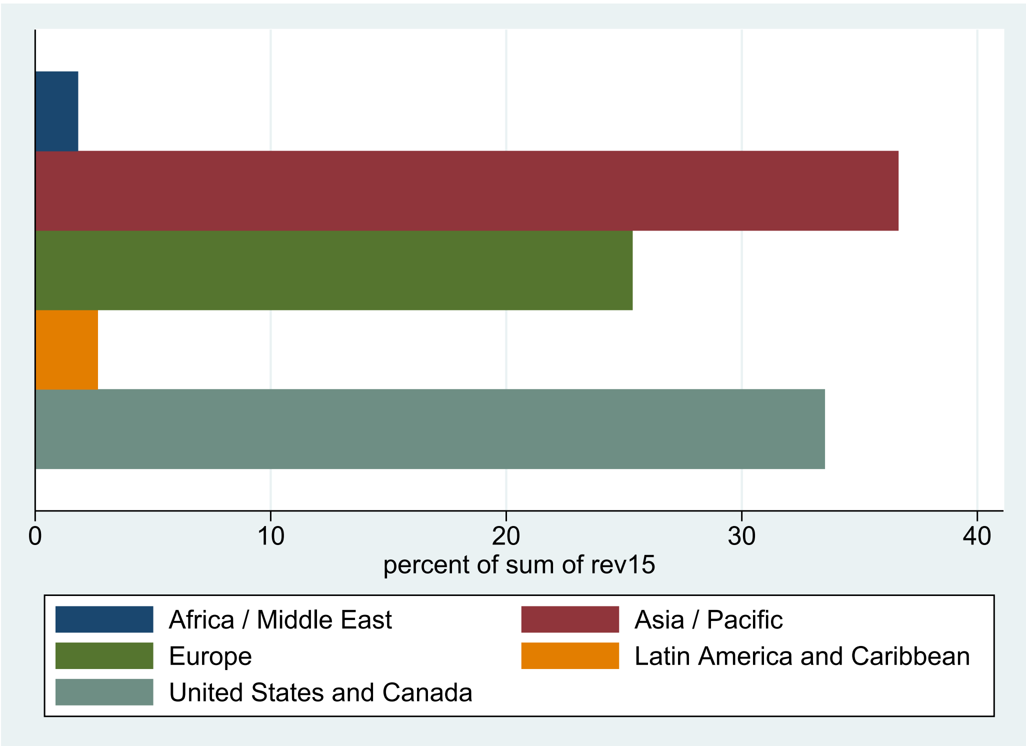
We also display the distribution of firms across sectors, in terms of both firm numbers and revenues respectively. The sectors are: consumer discretionary, consumer staples, energy, financial, health care, industrials, information technology, materials, real estate, telecommunication services and utilities.[20]

[20] Details of the industry classifications can be seen in Appendix.



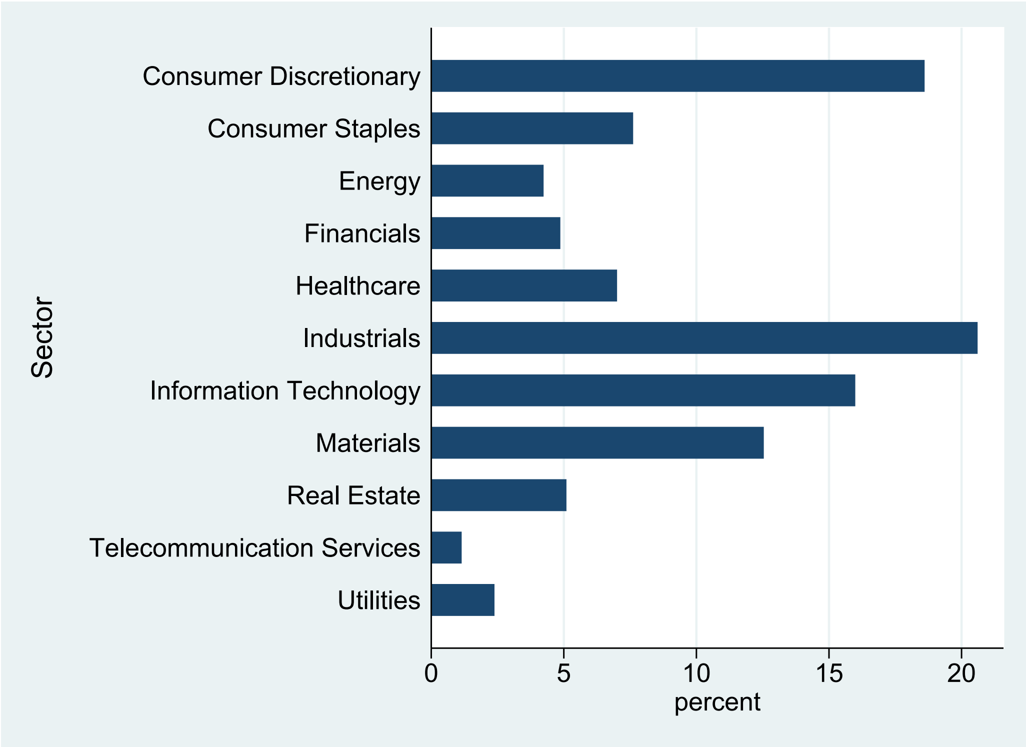
Notes: Data source: Capital IQ

Figure 33: Geographic distribution of firms



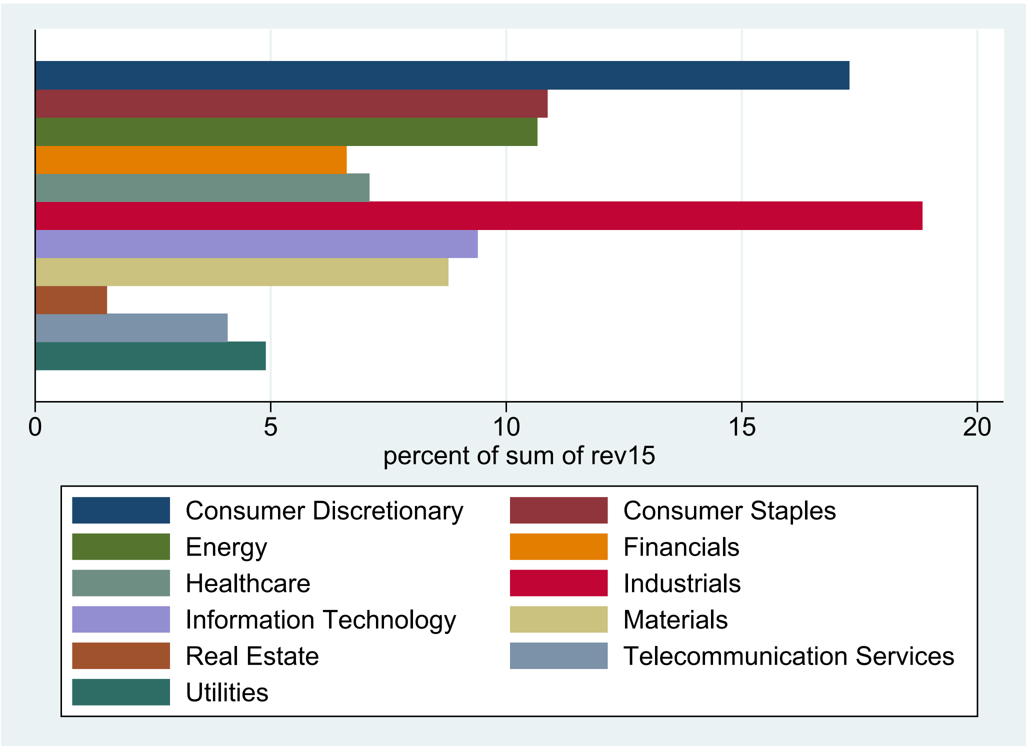
Notes: Data source: Capital IQ

Figure 34: Geographic distribution of firms



Notes: Data source: Capital IQ

Figure 35: Sector distribution of firms



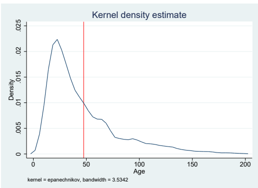
Notes: Data source: Capital IQ

Figure 36: Sector distribution of firms

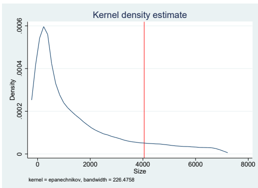
Next, we display some statistical characteristics of the firms in Table 30: age, size, latest revenue, profit and enterprise value. We include the mean, standard deviation, minimal value and maximal value of these variables. Moreover, we draw the probability distribution function (PDF) of these variables and productivity[21] in Figure 37. We can observe from the density functions that all the variables are fat-tailed distributed.[22]

Table 30: Summary Statistics I

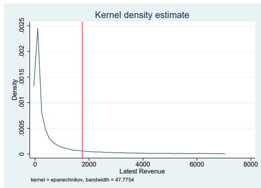
Variable	Mean	Std. Dev.	Min.	Max.	N
Age	17.5	39.3	1	772	19160
Latest Revenue	1756.9	8408.3	0	280289.8	19160
Latest Profit	533.2	2735	-1716.2	94823.8	19160
Size	4067.5	21528.3	0	627150	19160
Latest Total Enterprise Value	1500.2	9298.5	0	583465.3	19160



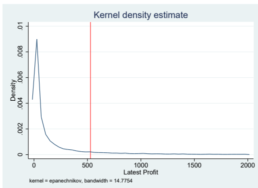
(a) Age



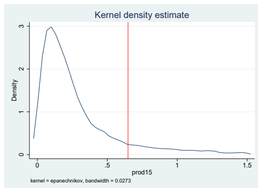
(b) Size



(c) Revenue



(d) Profit



(e) Productivity

Figure 37: Probability Density Function

.8.3 Descriptive Evidence

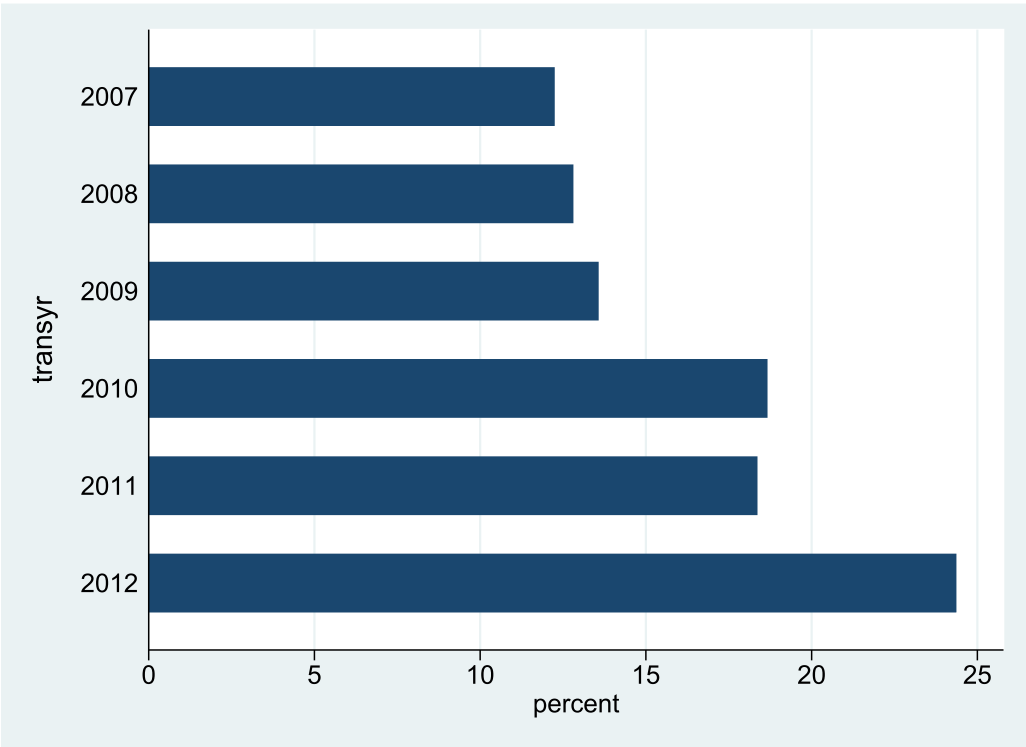
In this section, we display the features related to merger and acquisition (M&A). Instead of rushing to any of the analysis, we firstly enunciate the identification of M&A. In theory, M&A refers to the transactions in which the ownership of companies, other organizations or their operating units are transferred or combined, see Tirole (2006). In the data set, we only focus on the transactions which are recorded as "M&A" and also involve a change of ownership. In other words, we neglect those transactions labeled as merger and acquisition, however, do not end up with a change of control.[23]

[21] Productivity is estimated following the method of Loecker (2013).
[22] We present the right-truncated distribution of all variable.
[23] Some transactions can be labeled by security commission as "'M&A" even though they are not. For instance, tender offers, sometimes labeled as merger and acquisition, do not necessarily lead to a change of ownership. Or, increasing outstanding shares by a big shareholder may also be labeled as "M&A", even though the shareholder does not aim for it. The reason for this broad definition of M&A in reality is to reveal information. By doing so, the other shareholders will receive the message about the emergence of a new big shareholder, who might be a potential buyer of the company.

These real "M&A" takes up a percentage of 42.15% in all the "M&A" transactions in 2012.

Then, we display the features of M&A, including the prevalence of M&A in our sample, how it is distributed across regions and sectors, how it changes through time, and the performance of firms *ex ante* and *ex post*.

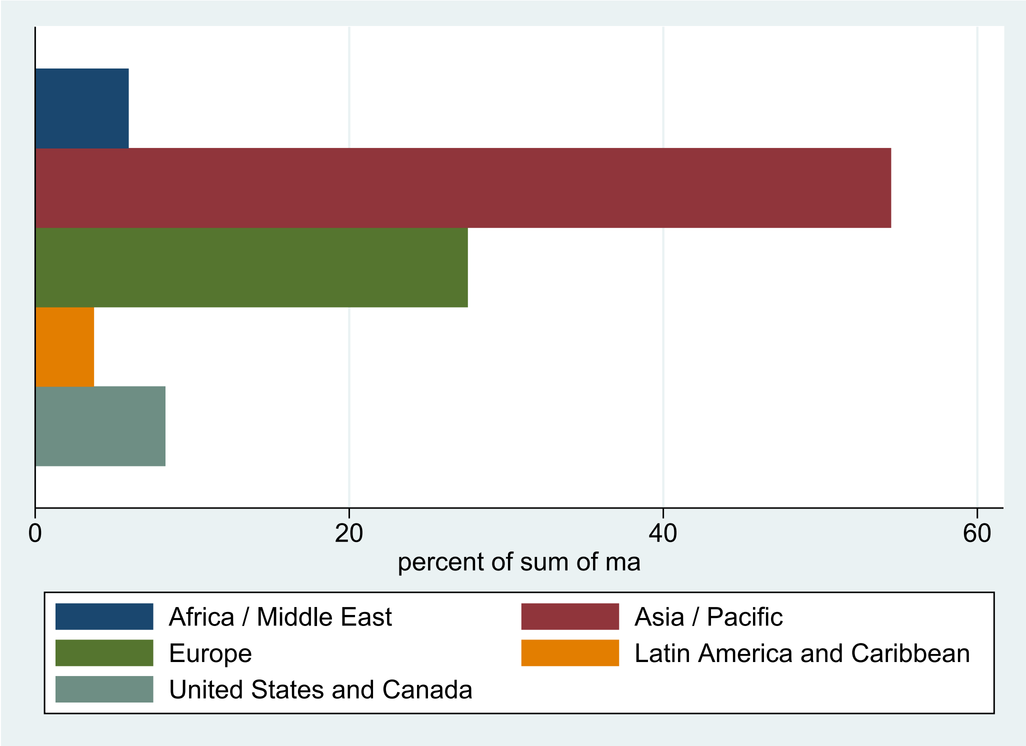
Among the total number of 19, 160 firms, an average percentage of 21.28% has been acquired by the other firms. Figure 38 represents the change of this percentage from year 2007 to year 2012. We can observe that M&A keeps increasing from year 2007 to year 2012.



Notes: Data source: Capital IQ

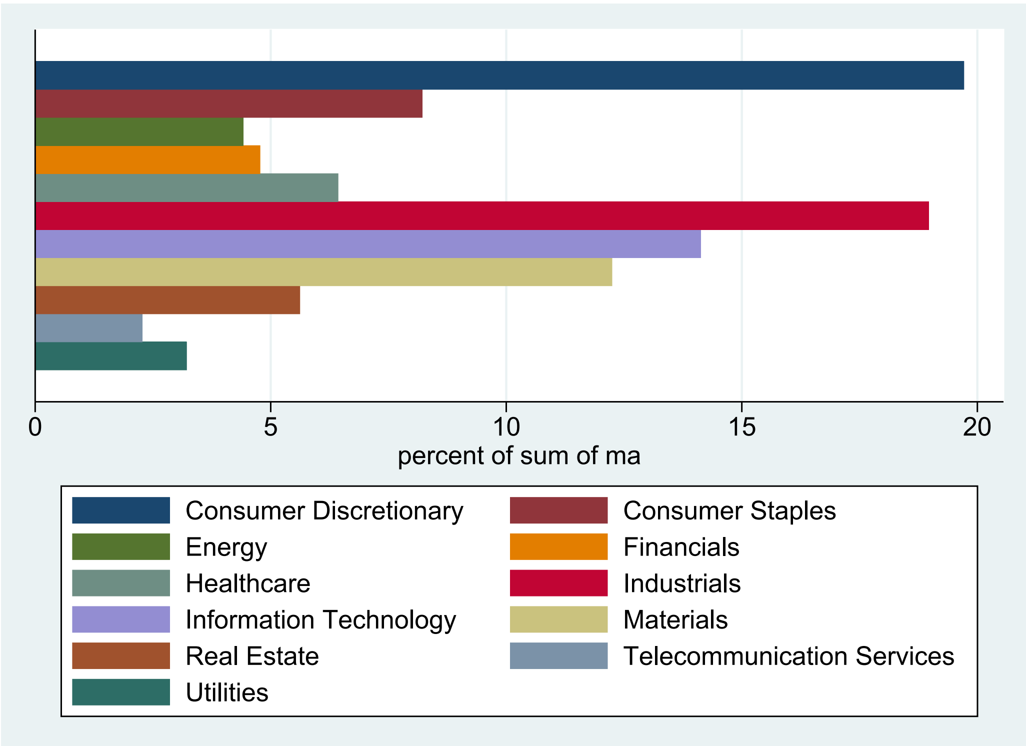
Figure 38: Percentage of the acquired firms

Next, we display the distribution of merger and acquisition transactions across region and sectors. Figure 39 and Figure 40 displays the distribution of mergers and acquisitions across regions and sectors, respectively. It is striking to see that the United States and Canada only takes up less than 10% of the total M&As. In comparison with that, Asia/Pacific takes up more than half of the M&As worldwide.



Notes: Data source: Capital IQ

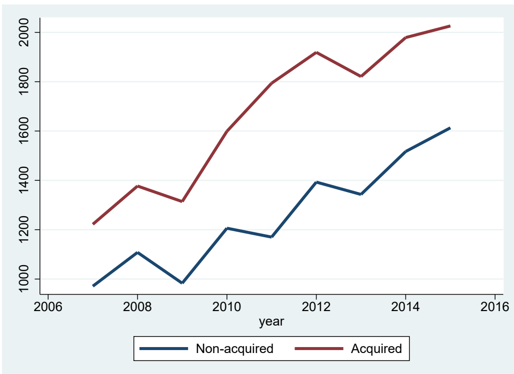
Figure 39: Sector distribution of firms



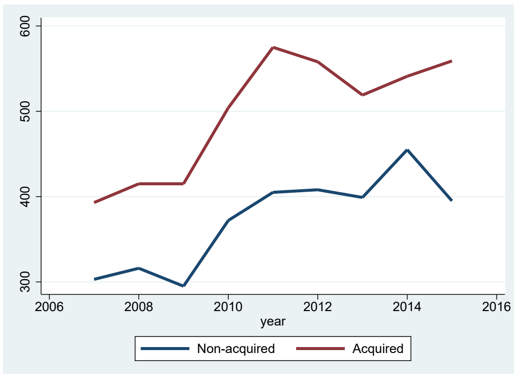
Notes: Data source: Capital IQ

Figure 40: Sector distribution of firms

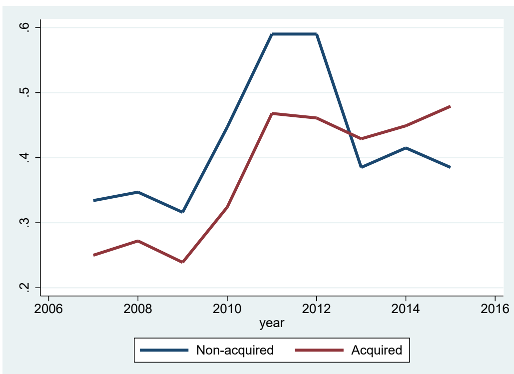
Then, we display the performance measures of firms *ex ante* and *ex post*, for both treated group and control group. For convenience, we restrict our treated group to firms which were acquired in year 2010, while the control group contains firms that did not involve in M&A in all years. The performance measures include revenue, profit and productivity. What we are interested in are firms' behaviors around 2010 as well as the difference between the two groups. First, let us focus only on target firms. We can observe from Figure 41 that acquired firms experienced boosts in their revenues, profits and productivities in year 2010 on top of the time trend. These three measures keep climbing afterwards, in spite of a mild drop in around 2012 to 2013. Second, let us compare the two groups. No matter *ex ante* or *ex post*, the treated group displays higher revenues and profits than the control group. This means that better firms get picked by the buyer company to be an acquisition target. But there is no obvious sign whether the difference is contracting or expanding *ex post*. However, productivity of the treated group was lower than the control group *ex ante* but surpassed it after three yeas of M&A. This will be further validated by an difference-in-difference (DID) method in Section 3.4. This result reveals the possibility that target firms might be those with high potential of growth and its buyer takes this into consideration when making the acquiring decision.



(a) Revenue



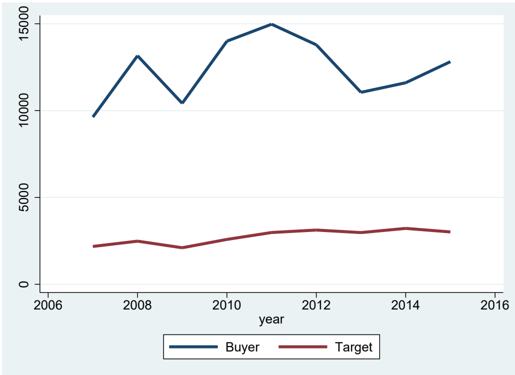
(b) Profit



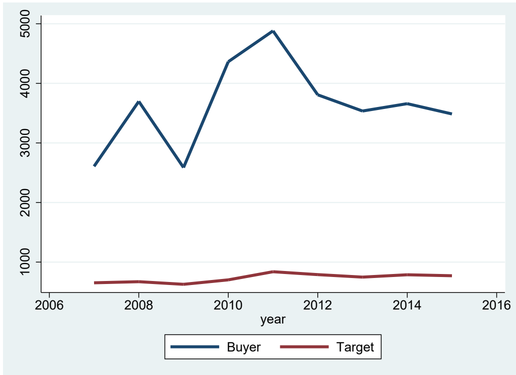
(c) Productivity

Figure 41: Performance Measures of Acquired and Non-acquired Firms

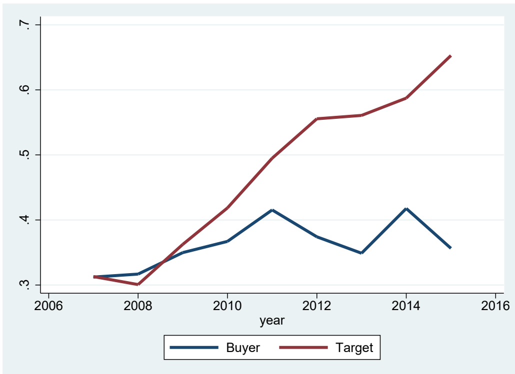
What is more, we also compare the target firms and its buyer firms in Figure 42. We find that target firms are not less productive than the acquiring firms. However, the acquired firms are much less profitable than acquiring firms. These finding echo an important stand in previous research that emphasized the role played by assortative matching, see McGuckin and Sang (1995), Rhodes-Kropf and Robinson (2008) and Syverson et al. (2015).



(a) Revenue



(b) Profit

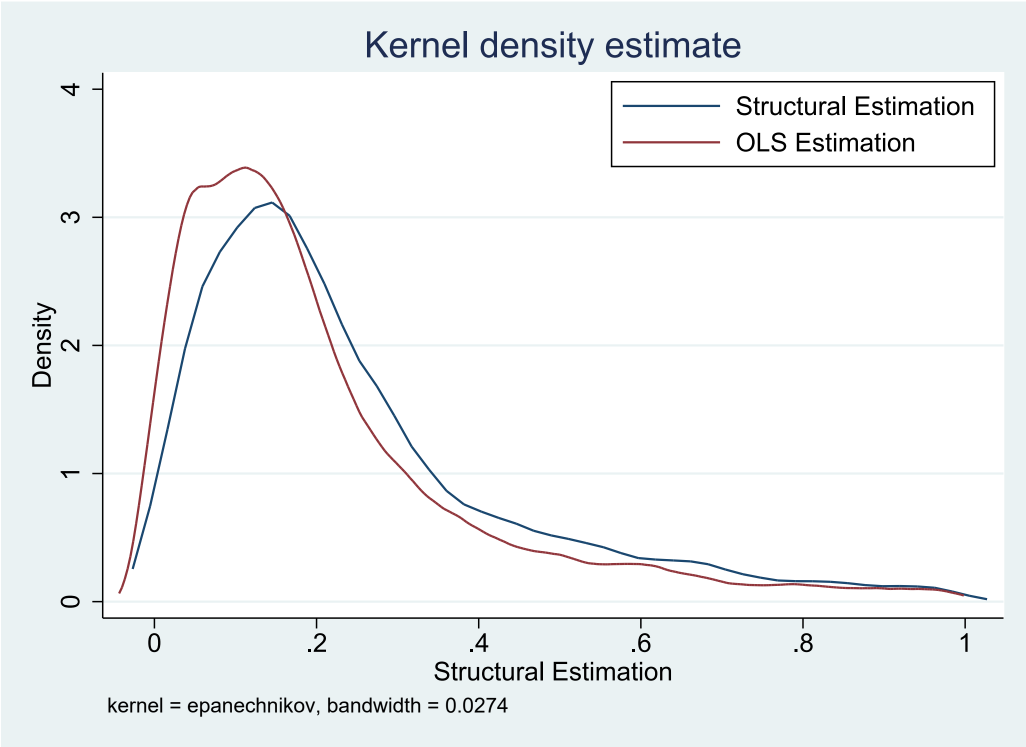


(c) Productivity

Figure 42: Performance Measures of Acquired and Non-acquired Firms

.9 Difference-in-Difference Analysis

.10 Productivity Estimation



Notes: Data source: Capital IQ

Figure 43: Productivity Estimation

Then we compare the difference of structural estimation result and OLS estimation result for acquired firms and non-acquired firms, respectively. The difference is defined as the following:

$$\frac{\hat{\varphi}_{OLS} - \hat{\varphi}_{structural}}{\hat{\varphi}_{structural}}$$

This difference is -2.75% for acquired firms and -7.52% for acquired firms.