ESSAYS IN EMPIRICAL MICROECONOMICS

A Dissertation

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ABSTRACT

This dissertation introduces two essays with the focus on alternative approaches to empirical research in economics. The first essay uses a reduced-form approach to address a "macro-phenomenon:" the long-standing puzzle of China's high household saving rate. The second essay employs a structural model to evaluate the social welfare of a procurement mechanism: the A+B auction.

In the first essay, we study the role of income inequality interacting with liquidity constraints in explaining the high household saving rate in China. The predictions implied by a simple lifecycle heterogeneous agent model are consistent with data facts. Using three large nationally representative data sets, China Household Finance Survey (CHFS), China Family Panel Studies (CFPS), and Chinese Household Income Project (CHIP), we find robust evidence that (1) the rich save more; (2) the poor are more likely to face liquidity constraints, and the effect of liquidity constraints on household saving rate is significantly positive; (3) income inequality has a significant positive effect on aggregate household saving rate; and (4) the marginal propensity to consume out of transitory income for poor households is significantly higher than for rich households. Our study provides a policy implication that economic policy of reducing income inequality would lower the aggregate saving rate and thus become a policy of economic transition and growth.

In the second essay, we investigate an innovative and widely used contracting mechanism, the A+B auction, in highway procurement projects. We introduce a structural model with time incentives/disincentives and construction uncertainties under which contractors' actual working days may deviate from the bidding days in the construction phase. This may make the A+B mechanism neither *ex-ante* nor *ex-post* efficient. We demonstrate that the model primitives including the contractor's cost function, distribution of private types, and incentive/disincentive parameters are all nonparametrically identified. Using the data from highway procurement auctions in California, we provide strong empirical evidence that

considering the existence of uncertainty in the structural analysis would lead to a significant efficiency loss. On average, the *ex-ante* (*ex-post*) welfare loss is 38% (37%) of the contract value. Counterfactual time incentive contracts under A design would decrease the *ex-ante* (*ex-post*) total costs by 26% (36%) of the contract value, with an average reduction of \$2.6 million (\$3.7 million).

DEDICATION

To My Parents and Parents-in-Law,

for your unconditional love and infinite supports along the journey.

To My Wife, Daughter and Upcoming Baby Boy,

I would never have been the person I am today without your countless inspiration.

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All other work conducted for the dissertation was completed by the student independently.

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1. GENERAL INTRODUCTION

The primary focus of the dissertation is to apply alternative empirical methods to address critical economic questions.

In the first paper, we investigate the role of income inequality interacting with liquidity constraints in explaining the high household saving rate in China. In a simple two-period model, households are heterogeneous in income and subjective discount factor, and whether the liquidity constraint is binding, consumption and saving rate are endogenously determined. The model generates several predictions consistent data facts: (1) the rich save more; (2) the proportion of constrained households for the poor is higher than that for the rich; (3) liquidity constraints would increase household saving rate. (4) when income inequality increases, the rich save even more, in the meanwhile, the poor would also save more due to the binding liquidity constraints, and thus the aggregate household saving rate would rise.

Using three sources of large, nationally representative household survey data, the China Household Finance Survey (CHFS), the China Family Panel Studies (CFPS), and the Chinese Household Income Project (CHIP), we provide direct empirical evidence implied by the theoretical model. We find that in China, (1) the top 20 percent permanent income households' saving rate is 19–23 percent significantly higher than the bottom 20 percent households'. (2) the bottom 20 percent permanent income households are more likely to face a borrowing constraint, with a 12–20 percent significantly higher probability; (3) the existence of liquidity constraints would lead to a significant increase of more than 20 percent in the household saving rate; (4) income inequality would have a significant positive impact on the household saving rate at the county level, with a 1 point on a scale of 100 measure increase in the Gini coefficient leading to an increase of 0.2 percent in the aggregate saving rate; (5) the estimated MPC for the top 20 percent households range from 200 to 400 RMB per 1000 RMB, while for the bottom 20 percent households, the range from 600 to 900 RMB per 1000 RMB.

These findings would have significant policy implications. The Chinese government's policies on reducing the saving rate have not yet produced substantial results. If income inequality and liquidity constraints were the key reasons for the high aggregate household saving rate, the resulting policy would be drastically different. For example, it is appropriate for the Chinese government to design some income redistribution programs (such as EITC) to reduce income inequality or devote more resources to support the credit market development. An economic policy of tackling income inequality would lower the aggregate saving rate, thus becoming a policy of economic transition and growth.

In the second essay, we study the A+B procurement contracts in the context of highway projects construction. We set up a structural model that features by time incentives/disincentives, externalities, and construction risks. We explain why contractors often do not complete the projects on time. This discrepancy may make the A+B mechanism neither ex-ante efficient nor ex-post efficient. We show that the model components (the marginal expediting cost function, the distribution of private type for contractors, and the incentive/disincentive daily rate) are all identified from the contract level and bid level data. We apply the model to analyze the data on the Caltrans auctions of highway procurement contracts. Our estimates provide substantial evidence that considering the existence of implement uncertainty in the structural analysis of bidding data leads to significant inefficiency.

2. INCOME INEQUALITY, LIQUIDITY CONSTRAINTS, AND CHINA'S HOUSEHOLD SAVING RATE

2.1 Introduction

Over the last three decades, the Chinese economy has been growing at an average annual rate of nearly 10 percent, and now it becomes the second largest economy in the world. One of the unique features of Chinese economy is the high and rising household saving rates: China's aggregate household saving rate has exceeded 35 percent in the recent decade, which is one of the highest in the world.[1] China's high household saving rate may already have real implications for the world economy. In 2005, Ben Bernanke, then a governor of the Federal Reserve Board, argued that China's large surpluses have adverse effects on richer countries' current accounts and financial markets. In fact, another unique feature of the Chinese economy over the same period should not be ignored: China's household income inequality has been among the world's worst.[2] Put them together, between 1992 and 2015, China's household saving rate has been increasing steadily from 33.98 to 37.07 percent, in the meanwhile, Chinese households income inequality measured by the Gini coefficient has also risen from 0.390 to 0.462.[3] Are the two simultaneously existing unique features of Chinese economy correlated? In this paper, we examine the role of income inequality interacting with liquidity constraints in explaining the high household saving rate in China.

To date, there are some compelling explanations on the "Chinese Saving Puzzle" (first refered by Modigliani and Cao, 2004) in the literature, including (1) demographic changes (Modigliani and Cao, 2004; Horioka and Wan, 2007; Curtis, Lugauer, and Mark, 2015; İmrohoroğlu, Zhao, et al., 2017; Choukhmane, Coeurdacier, and Jin, 2013; Ge, Yang, and Zhang, 2012); (2) precautionary saving motives (Meng, 2003; He, Huang, Liu, and Zhu, 2017; Chamon and Prasad, 2010; Wang and Wen, 2012); (3) gender imbalance and competitive mo-

[1] See panel (1) of Figure A.1 in Appendix.
[2] See panel (2) of Figure A.1 in Appendix.
[3] See Figure A.3 in Appendix.

tives (Wei and Zhang, 2011); (4) high income growth and habit formation (Horioka and Wan, 2007), co-residence effects (Rosenzweig and Zhang, 2014), financial choices (Cooper and Zhu, 2017).[4] No consensus has emerged, and the puzzle remains.

The main contribution of this paper to the literature on China's household saving rate is that we make the first endeavor to bridge income distribution with China's household saving rate and provide consistent and comforting micro-level evidence. Inspired by the literature on heterogeneous agent model in macroeconomics (Aiyagari, 1994; Achdou, Han, Lasry, Lions, and Moll, 2017), we build up a simple two-period model which links household saving rates to income inequality and liquidity constraints. Specifically, in this model, households are assumed to be different in two dimensions: (i) heterogeneity in initial wealth and flow income, with a particular case of two types, the rich and the poor; (ii) heterogeneity in time preference thereby in subjective discount factor, with a particular case of three types, the impatient, the less patient, and the patient. Also, we assume that households may face liquidity constraints.[5] Given a household's type of income and discount factor, whether the liquidity constraint is binding, consumption and saving rate are endogenously determined in the model. With this simple model, we provide several implications consistent with data facts: (1) the rich save more; (2) the proportion of constrained households for the poor is higher than that for the rich; (3) Liquidity constraints would increase household saving rate. (4) when income inequality increases, the rich save even more, in the meanwhile, the poor would also save more due to the binding liquidity constraints, and thus the aggregate household saving rate would rise.

Using three sources of large, nationally representative household survey data, the China Household Finance Survey (CHFS), the China Family Panel Studies (CFPS), and the Chinese Household Income Project (CHIP), we provide direct empirical evidence implied by the

[4]For a a comprehensive review of the facts and explanations pertaining to China's saving, see Yang, Zhang, and Zhou (2012).

[5]Stiglitz and Weiss (1981) indicate that as long as the institutional barriers (such as a lack of consumer credit, or capital market imperfections leading to credit rationing) are present, there will be liquidity constraints in the economy. Financial development in China, although has been improving over the past decades, is still underdevelopment. Thus, assuming liquidity constraints exist is reasonable.

theoretical model. First, we regress the household saving rate on current income quintile dummies to estimate the differences in the saving rate between higher income quintile and the lowest. We find a robust positive relationship between the saving rate and current income across all income classes in all three data sets. For example, for the CHFS, the estimated increments in the median household saving rate range from 30 percent in the second lowest income quintile to above 70 percent in the highest, and they are strictly increasing from the lowest income quintile to the highest. We continue to find a highly significant positive association when using subsample regressions and three years average income to correct the endogeneity problem for the current income. Estimated saving rate differences range from 35 percent to 82 percent in the CHFS for the subsample regressions, and from 5 percent to 19 percent for the average income approach. The positive relationship is even more pronounced when we exclude high-income entrepreneurs, drop younger households (below age 60), use an alternative definition of saving rate as a dependent variable, and apply per capita income to redefine income quintiles. Overall, in China, the top 20 percent permanent income households' saving rate is 19–23 percent significantly higher than the bottom 20 percent households'.

We then exploit the probit regression to examine if poor households are more likely to face liquidity constraints. We use two ways to measure whether or not household i is facing a liquidity constraint, that is, the variable $\texttt{LC}_i = 1$. One is the definition in Zeldes (1989a), which states that a household is liquidity constrained if the total value of financial assets is less than two months permanent income. Another is directly from our CHFS questionnaire, which asks respondent "Does your family have any credit cards, excluding inactivated cards?" Our estimates indicate that estimated marginal effects of the income quintiles on the probability of facing liquidity constraints range from 2 percent for the quintile 4 to 10 percent for the quintile one using measure the first definition in the CHFS. The effects are even more significant when using the second measure. In sum, the bottom 20 percent permanent income households are more likely to face a liquidity constraint, with a 12–20 percent significantly higher probability.

To evaluate the effect of liquidity constraints on the saving rate, we design a difference-in-difference approach (DID) applying to the CHFS and the CFPS. Only the households that are credit constrained in 2013 (2012) from CHFS (CFPS) data are used as the whole sample. We separate them into two groups: treatment group, defined as the unconstrained households in the year 2015 (2014), and the comparison group, defined as the constrained group in the year 2015 (2014). We show that the existence of liquidity constraints would lead to a significant increase of more than 20 percent in the household saving rate.

Next, we address the research question what the general equilibrium effect of the aggregate household saving rate from a rise in the income inequality. We perform the cross-sectional regression that links the calculated county-level aggregate saving rate to the measure of income inequality for all three data sets, controlling for location fixed effects and other factors. We find, in the CHFS, that income inequality would have a significant positive impact on the aggregate household saving rate at the county level, with a 1 point on a scale of 100 measure increase in the Gini coefficient leading to an increase of 0.2 percent in the aggregate saving rate.

Finally, we provide empirical evidence that the marginal propensity to consume out of both the permanent income and transitory income would be significantly different across income classes for all three data sets. Although we do not see a diminishing MPC with income classes, there is still an essential pattern that the MPC out of both types of income for the bottom 20 percent households are much higher than that for the top 20 percent households. The estimated MPC for the top 20 percent households ranges from 200 to 400 RMB per 1000 RMB, while for the bottom 20 percent households, the range from 600 to 900 RMB per 1000 RMB.

These empirical pieces of evidence would have significant policy implications. The Chinese government's policies on reducing the saving rate have not yet produced substantial results. If income inequality and liquidity constraints were the key reasons for the high aggregate household saving rate, the resulting policy would be drastically different. For example, it is appropriate for the Chinese government to design some income redistribution programs (such as EITC) to reduce income inequality or devote more resources to support the credit market development. An economic policy of tackling income inequality would lower the aggregate saving rate, thus becoming a policy of economic transition and growth.

Related literature

According to the life-cycle hypothesis (LCH), the basic idea about demographic explanation is that a decrease in the non-working population, which consists of the young and the old, would increase household savings due to the "less mouths to feed". Besides, China has a long historical tradition of children taking care of their elder parents. As a result, since the one-child policy was introduced in 1979, increased savings were not only due to the reduction in young population but also viewed as an effective substitute for children ("old-age security"). Using a ratio of working population to the number of nonworking ("minors") as a proxy to the demographic change, Modigliani and Cao (2004) find that increased China's household saving rate over the period from 1953 to 2000 can be well explained by the increased ratio of employed population to nonworking population, mainly driven by the decrease in the young dependent population. Besides, Curtis, Lugauer, and Mark (2015) conduct a quantitative overlapping generations model and also provide some evidence supporting the link between demographics and the saving rate at the aggregate level. However, applying panel data analysis and separately considering the young dependent ratio and the old dependent ratio, Horioka and Wan (2007) finds that the changes in those ratios do not go very far in explaining China's provincial household saving rate for the period 1995–2004. Using the data from the Urban Household Survey (UHS), Chamon and Prasad (2010) reach a similar conclusion: there is no significant effect of the demographic shifts in China's household saving rate. Recent work about the demographic explanations focus on bridging the micro-level mechanism with the macro-level framework and provide some micro-evidence (see, e.g., İmrohoroğlu, Zhao, et al., 2017 and Choukhmane, Coeurdacier, and Jin, 2013).

One concern about the demographic explanations lies in that demographic shift is not static but dynamic. As the age population move over time, we would not see a consistently high and even rising household saving rate. In fact, since 2000, Chinese household saving rate has been rising rapidly and hit the highest point in the history.

The precautionary saving motives argue that people who are not covered by a social safety network tend to have precautionary saving motives and thus save more for unexpected events (Giles and Yoo, 2007). Although the Chinese economy has experienced rapid growth since the reform and opening up, due to lack of a safe social security and insurance network and increasing costs on education, housing, and healthcare, etc., make Chinese household tend to save more to respond the income and expenditures uncertainties in future. On the income uncertainties side, Meng (2003) examine the role of precautionary saving in Chinese urban households during the period from 1995 to 1999. She finds that not only the Chinese urban households ever experienced past income uncertainties tend to have increased propensity to consume, but for households without unemployed members, the income uncertainty has an even stronger effect on saving. Using China's reform of the state-owned enterprises (SOE) in the late 1990s as a natural experiment, He, Huang, Liu, and Zhu (2017) also show that the precautionary saving motive does exist in Chinese households. Using the CHFS, however, our preliminary results show that the saving rate of households whose heads work in government entities, public-sector organizations and state-owned enterprises are slightly and insignificantly higher (0.04 percent higher) than that of households whose heads work in privately-owned enterprises, collectively-owned enterprises, and foreign-funded enterprises. This result shows that China's gradually well-established labor law and law of employment contracts makes income uncertainty a less influential factor for the increasing household saving rate. On the expenditure uncertainties side, Chamon and Prasad (2010) argue that uncertainty in expenditures, particularly on education, housing, and healthcare, may generate high aggregate savings for the young and the elderly. Over the last decade or so, however, the social insurance system has been firmly established. There is almost universal health insurance coverage, and rapid retirement insurance coverage has not lowered the saving rate. Also, there is no consensus as to whether the high housing prices can explain the high household saving rate (Wang and Wen, 2012).

Another compelling explanation is the imbalanced sex ratio and competitive motive. The idea is built on the traditional culture of son preferences in Chinese households: as sex ratio increase, Chinese households tend to save more to improve son's competitiveness in the marriage market. Using household-level data, Wei and Zhang (2011) find that saving rates for the households with sons in the high sex ratio county is significantly higher than for the households with sons in the low sex ratio county in both rural and urban sample. At the provincial level, they find evidence that the sex ratio has a significant positive effect on the provincial aggregate household saving rate. They argue that during 1990–2007, the factor can account for at least 60 percent actual increase in China's household saving rate. However, we reexamine the competitive saving motives using the same data sources as they did and find the evidence may be not robust. First, although we find the similar effects of the sex ratio on household saving rates using the sex ratio from the 1990 census when using the sex ratio from 2000 census, the effects vanish. Second, even using the ratio from 1990 census, the effects exist only in the rich households sample and rich counties sample. For the poor households and poor counties, the estimates are significantly negative and statistically insignificant, respectively.

There are other explanations for Chinese household saving rate. According to Carroll and Weil (1994), the rising household savings may be due to a consequence of high-income growth and habit formation. Horioka and Wan (2007) find that the lagged saving rate has a significant positive effect on the provincial-level household saving, which is consistent with the existence of inertia or persistence. However, as argued in Modigliani and Cao (2004), during the 1950s to the mid-1970s, average Chinese household saving rate was lower than 5 percent, which implies that the Chinese cultural, ethical values of "thrifty" counts little if any. Cooper and Zhu (2017) estimate a structural life-cycle model to study household finance in China. They find that the high Chinese household raving rate is mainly driven by the labor market risk and the patient Chinese households. Other studies, such as Ge, Yang, and Zhang (2012), Rosenzweig and Zhang (2014), and Song and Yang (2012), focus on explaining another feature of Chinese household saving rate, the "U–shaped" age-saving profile started with Chamon and Prasad (2010).

Roadmap

The rest of this chapter is organized as follows. Section 2.2 presents the data and stylized facts of Chinese household saving rates. In Section 2.3, we introduce our theoretical model that links income inequality, liquidity constraints and saving decisions in a two-period lifecycle model. Section 2.4 describes the empirical methodology. The results and analysis are presented in Section 2.5. Section 2.6 concludes. The Appendix contains proofs, figures, tables, and other details.

2.2 Data

In this section, we provide data pieces of evidence that motivate the idea that income inequality interacting with liquidity constraints matter in the explanation about China's high household saving rate, based on various household survey data sources from China. First, we plot the household saving rates by income class. The data pattern is consistent with various data sources. Second, we take a look at the household saving rate by income group and note, within each income group, the importance of facing a liquidity constraint on household saving rates. Finally, we show the relationship between the county-level aggregate household saving rate and the county Gini coefficient. These data facts motivate the theoretical model in the next section and the reduced form analysis in the following section.

2.2.1 Data sources

We use three data sets from China in the analysis. The data are drawn from the China Household Finance Survey (CHFS), the China Family Panel Studies (CFPS), and the Chinese Household Income Project (CHIP).

The CHFS is our primary source of data used in the analysis. It is a large, nationally representative and longitudinal data set, conducted by the Survey and Research Center for China Household Finance at Southwestern University of Finance and Economics in Chengdu, China. The survey was first launched in 2011, and another three waves were conducted in 2013, 2015, and 2017, respectively. The CHFS uses a three-stage stratified sampling method and covers 29 provinces and autonomous regions (except Tibet, Xinjiang, Hong Kong, Macao and Taiwan). It also has a low non-response rate compared to other survey data. The overall representativeness of the CHFS is excellent, and it fits our research purpose well. Besides, the survey contains detailed information about a large sample of individuals and households' demographic characteristics, assets and liabilities, insurance and social welfare, and income and expenditures. So thus the CHFS is particularly suited to our purposes. We primarily use the 2013 and 2015 waves in this study.

The CFPS, conducted by the Institute of Social Science Survey at Peking University, China, is also a nationally and representative longitudinal data set. The survey started in 2010, and the following three waves were in 2012, 2014, and 2016. The primary purpose of the survey is to track individuals, families, and communities in contemporary China. Although the CFPS focuses on various aspects of social life, it also collects wealth information about incomes and expenditures. It fits our research purpose well. Among the current four waves, the 2012 and 2014 waves are used in the analysis.

The CHIP is nationally representative data set conducted in 1988, 1995, 2002, 2007, and 2013. The five waves of the survey are designed to track the dynamics of income distribution of Chinese individuals and households in both urban and rural area, and thus it also contains sufficient information about incomes and expenditures. The 2013 wave is used in the study.

We apply the same criteria in all three data sets to construct our estimation sample. First, we remove outliers and households with missing data, the 2015 CHFS survey provides a sample of 21,861 urban households from 1,048 different communities in 262 counties; the 2014 CFPS survey has a total 6,603 urban sample from 1,413 distinctive communities in 358 counties; the 2013 CHIP survey data include a total 6,674 urban sample from 212 counties. Survey participation was randomized; so, again, the data are highly representative regarding the geographic location and economic development. For panel exercise in our paper, we use both three-years panel and two-years panel, and the matching households from 2013 and 2015 of CHFS data reduces the sample size to 13,120; the matching sample size is 10,677 for the 2012 and 2014 CFPS survey. We use the 2013 CHIP survey data only to perform the cross-section analysis because of the long time span for the recent CHIP survey.

2.2.2 Data evidence

Income-saving rate profile

We first summarize China's uneven distribution of household saving rates across income level. Additionally, we plot Chinese households by income classes. These pieces of evidence together show the first of total four facts: not every Chinese household saves; the high-income households' savings account for a much larger fraction of total savings, with very high household saving rates.

Table A.1 shows household saving rates by income classes and shares of savings for each income class, calculated from our three data sets CHFS 2015, CFPS 2014, CHIP 2013, and the National Bureau of Statistics of China (NBS). According to the CHFS 2015 data, Chinese households have an aggregate saving rate of 29.1 percent, which is slightly higher than the level of 28.5 percent from the NBS of China. It is also consistent with both the available macro data and microdata used in other studies (see Zhou, 2014 and Banerjee, Meng, Porzio, and Qian, 2014, for example). The aggregate saving rate for urban households and rural households are 37.3 percent and 11.6 percent, respectively. Also, not every household saves in the CHFS 2015 sample, however, as about 44.1 percent of households did not save. More important, the distribution of saving rates is extremely uneven across income classes. The top 1 percent of income households' total savings account for nearly 70 percent of total household savings, with an extraordinary high saving rate of 86.6 percent. The top 5 percent of income households have an average saving rate of 74.1 percent, with the share of the total savings for these households are over 99 percent of total savings. The saving rate for the top 10 percent and top 25 percent of income group households are 67.2 percent and 56.9 percent, respectively. As an opposite, for the bottom 50 percent of income households, their saving rates and the shares of savings are even negative, with –132.7 percent and –45.8 percent, respectively.

The fact that household saving rate is greater for the higher income class than that for the lower income is robust in the CPFS 2014 and CHIP 2013. In the CFPS 2014, the aggregate rate goes down from 58.1 percent for the top 1 percent of income class to –45.8 percent for the bottom 50 percent income class. Moreover, the saving rate decrease to 1.7 percent for the bottom 50 percent of income class from 53.6 percent for the top 1 percent of income in the CHIP 2013. Additionally, the savings shares for the top 1 percent of income class own 44 percent of total savings in the CFPS 2014 and 12.2 percent of total savings in the CHIP 2013. Figure A.2 displays that Chinese households saving rate by income percentile increases as income level rises for CHFS 2015 (panel 1), CFPS 2014 (panel 2), and CHIP 2013 (panel 3).

Saving rate and liquidity constraints

Next, we show evidence about the role of liquidity constraints on households saving rates, by comparing households saving rates for those who may be constrained with those who may be not across different income classes. In particular, we exam households whose income are above top 20 percent, below bottom 20 percent, and in the middle. For the measures of constrained household, we use the one in (Zeldes, 1989a) and the credit card usage to define whether or not a household is facing liquidity constraint. Table A.2 shows a summary for CHFS 2015, CFPS 2014, and CHIP 2013.

Among 5179 urban households in CHFS 2015, there are 4330 (83.61 percent) households in the top 20 percent, 501 (9.67 percent) households in the bottom 20 percent, and 293 (5.66 percent) households in the middle. The first three columns in the panel (a) of Table A.2 uses the definition in the literature (Zeldes, 1989a) and the last three uses the credit card usage measure. We find that in the top 20 percent of income group, about 17 percent households are facing a liquidity constraint, and the corresponding saving rate is about 78 percent, which is about 40 percent higher than those who are not facing a liquidity constraint in the same income group. For the middle-income group, the percentage of constrained households goes up to near 32 percent, with the saving rate for constrained households is 13 percent, which is also higher than that for those unconstrained households in the group. The proportion of constrained households in the bottom 20 percent is even higher to 38 percent. The saving rate for the constrained households is still higher than that for unconstrained households, even though it is a negative number. Similarly patterns can be found in the panel (b) and (c) for CFPS 2014 and for CHIP 2014, respectively. There are more households may face a liquidity constraint for the bottom 20 percent of income group than that for the top 20 percent of income group. Moreover, within each income group, the saving rate for the constrained households tend to be higher than that for the unconstrained counterpart in each income bracket.

Aggregate household saving rate and the Gini coefficient

Finally, we look at data regarding the relationship between aggregate saving rate (both the country-level and the county-level) and the Gini coefficient. Figure A.3 displays the simple time-series trend for the aggregate household saving rate and the Gini coefficient from 1994 to 2015. The household aggregate saving rate increased steadily from 34 percent in 1992 to 37 percent in 2015, in the meanwhile, the Gini coefficient rose dramatically from 0.39 in 1992 to 0.46 in 2015. Except for some periods, the Gini coefficient exhibits a similar trend to that of the household aggregate saving rate.

In addition, Figure A.4 shows the simple cross-sectional patterns between the county-level aggregate household saving rate and the county-leve Gini coefficient. Panel (1) of Figure A.4 simply suggests that a county with a higher Gini coefficient may have a higher aggregate saving rate for CHFS 2015, even though the pattern seems to be not clear in the panel (2) for CFPS 2014 and (3) for CHIP 2013.

To summarize, in this section, as expected, we show that (1) the aggregate household saving rate is high in China; however, not all households saved, with 44 percent of households not saving (CHFS 2015). The distribution of household saving rate is extremely uneven. The rich tend to save more. The saving rate of the top 1 percent of income households is much higher than that for the bottom 50 percent of income group households; (2) Chinese households may face a liquidity constraint. Comparing to the top 20 percent of income households and the middle-income group households, there is a larger proportion of households in the bottom 20 percent of income group facing a liquidity constraint. Moreover, the constrained households' saving rate is higher than the unconstrained's across income classes; (3) at county-level, the aggregate saving rate may be higher for the county with higher Gini coefficient. These pieces of data patterns are robust to various sources of data sets.

2.3 A Simple Heterogeneous Agent Model of Saving

In this section, we formulate a simple two-period endowment economy with heterogeneous households in time preference, wealth and income. The parsimonious model leads to several analytic results of household saving behavior that are consistent with data evidence presented in the previous section. That is, the rich tend to save more; the poor are more likely to face a liquidity constraint; the existence of liquidity constraints leads to a higher saving rate; a higher level of income inequality may lead to a higher level of aggregate household saving rate.

2.3.1 Preference and the constraints

An individual maximizes life-time utility drawn from the consumption c_t at each period t, $t = 1, 2$

$$u = log(c_1) + \beta \cdot log(c_2) \tag{2.1}$$

where $log(c_t)$ is the per-period utility function, and $\beta \in (0, 1)$ is the subjective discount factor. The budget constraints for the household obeys

$$c_1 + w_1 = w_0 + y_1 \tag{2.2}$$

$$c_2 = (1 + R) \cdot w_1 + y_2 \tag{2.3}$$

where w_0 denotes the initial level of wealth, w_1 represents the level of wealth to carry between "now" and "the future", y_1 and y_2 are the income received today and tomorrow, respectively, and r is the net real interest rate. We assume that there is no income growth, that is, $y_1 = y_2 = y$.

In addition to the budget constraints 2.2 and 2.3, households may also face a liquidity constraint

$$s_1 \geq -\frac{\tau \cdot y_2}{1 + R} \tag{2.4}$$

where s_1 denotes the saving plan and $\tau \in [0, m]$ measures the degree of constrained.[6]

Notice that this is a two-period model in which individuals will die at the end of the second period. We do not consider the bequest saving motive in the last period (even though it could be more realistic in real life and also be important in theory). Since caring about nothing afterward, individuals will consume all the available resources in hands, and there is no savings or wealth left.

2.3.2 Heterogeneity

We assume that individuals are heterogeneous in two dimensions: (i) their initial wealth w_0 and income y_t and (ii) their subjective rate of discount factor β. First, we consider two wealth and income types, the rich (denoted by r) and the poor (denoted by p). Let w_0^k and y_t^k denote the initial wealth and income for the k class, where $k \in \{r, p\}$. And the wealth

[6]This condition ensures non-negative consumption in the second period. When $\tau = 1$, it is actually so-called "natural borrowing limit" as discussed in Aiyagari (1994).

and the income for the rich and the poor satisfy

$$w_0^r = \theta_w \cdot w_0^p$$

$$y_t^r = \theta_y \cdot y_t^p$$

where θ_w and θ_y are the ratio of wealth to income for the rich and the poor, respectively.

Second, we assume that there are three types of household in terms of the subjective discount factor: impatient household with $0 < \beta_L \leq \beta_r$; less patient household with $\beta_r \leq \beta_M \leq \beta_p$; and patient household with $\beta_p \leq \beta_M < 1$.

2.3.3 Household decisions and the model predictions

The individual household's optimal consumption can be solved by maximizing the lifetime utility function 2.1, subject to budget constraints 2.2 and 2.3, and the borrowing constraint 2.4, given the exogenous wealth and income, the discount factor, and the interest rate. Since there are three levels of subjective discount factor and two levels of initial wealth and income, there are total six types household in this model economy: (1) rich–impatient household, (2) rich–less patient household, (3) rich–patient household, (4) poor–impatient household, (5) poor–less patient household, and (6) poor–patient household.

For each type of household, the interior solution (that is, the borrowing constraint is not binding) for optimal consumption satisfies the intertemporal Euler equation, and the assumption of log utility function implies that the current optimal consumption is a linear function of the present value of lifetime resources, with a fixed proportion

$$c_1^k = \frac{1}{1+\beta^j}(w_0^k + y^k + \tau \cdot \widetilde{R} \cdot y^k). \tag{2.5}$$

It follows from Equation (2.5) that household's current optimal saving is

$$s^k = \left(1 - \frac{1+\tau \cdot \widetilde{R}}{1+\beta^j}\right) y^k - \frac{1}{1+\beta^j} w_0^k. \tag{2.6}$$

If the borrowing constraint is binding, then the kinky solution for the current optimal consumption is

$$c_1^k = (1 + \tau \cdot \widetilde{R}) \cdot y^k. \tag{2.7}$$

Whether the household is facing the borrowing constraint depends on wealth/income group and patient degree. To characterize the equilibrium, we introduce the following assumption

Assumption 1. *(a) Assume that the initial wealth gap between the rich and the poor is smaller than the permanent income gap between them, that is, $\theta_w/\theta_y < 1$. (b) The cutoff values of β are given by following equations*

$$\beta_r = \frac{\rho_r + 1 - \tau \cdot \widetilde{R}}{1 + \tau \cdot \widetilde{R}}$$
$$\beta_p = \frac{\rho_p + 1 - \tau \cdot \widetilde{R}}{1 + \tau \cdot \widetilde{R}}$$

where $\rho_k = \frac{w_0^k}{y_1^k}$, $k \in \{r, p\}$ and $\widetilde{R} = \frac{1}{1+R}$.

This assumption implies that the initial wealth-permanent income ratio for the rich is smaller than that for the poor, that is, $\rho_r < \rho_p$. Figure A.5 displays the data evidence that motivates us. Optimal consumptions and savings for different types of household can be summarized in the following proposition.

Proposition 1. *Under Assumption 1, (1) for the rich-impatient, the poor-impatient, and the poor-less patient household, the borrowing constraint is binding and thus the current optimal consumption*

$$c_t^{r,L} = (1 + \tau \cdot \widetilde{R}) \cdot y^r, \quad \textit{for the rich-impatient household,}$$

and

$$c_t^{p,j} = (1 + \tau \cdot \widetilde{R}) \cdot y^r, \quad \textit{for the poor-j household}, j \in \{L, M\};$$

(2) for the rich-less patient, the rich-patient, and the poor-patient household, the borrowing constraint is not binding and thus the current optimal consumption

$$c_t^{r,j} = \frac{1}{1+\beta^j}(w_0^r + y^r + \tau \cdot \widetilde{R} \cdot y^r), \quad \textit{for the rich-j household}, j \in \{M, H\},$$

and

$$c_t^{p,H} = \frac{1}{1+\beta^H}(w_0^p + y^p + \tau \cdot \widetilde{R} \cdot y^P), \quad \textit{for the poor-patient household.}$$

These analytic solutions are useful to convey simple predictions that are consistent data evidence presented in Section 2.2. Those model predictions are summarized as follows:

(1) The rich tends to save more.

(2) Among the poor household, there is a larger fraction of households facing the borrowing constraint than that among the rich households.

(3) The existence of liquidity constraints lead to a higher aggregate household saving rate.

(4) Increasing the current income inequality would make the aggregate household saving rate even higher.

2.4 Empirical Strategies

In light of the theoretical model in Section 2.3, we construct and estimate several empirical models to study: (i) do the rich save more? (ii) are the poor more likely to face the liquidity constraints, and do the liquidity constraint leads to a higher saving rate? (iii) whether or not, at the aggregate level, income inequality will have a positive effect on the household saving rate? (iv) does the marginal propensity to consume (MPC) decreases with income level?

2.4.1 Income and saving rate

Econometric specification

Following Dynan, Skinner, and Zeldes (2004), we consider the following empirical specification

$$\texttt{saving rate}_i = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{D}_{\mathrm{incG}_i} + \boldsymbol{\gamma} \cdot \boldsymbol{X}_i + \epsilon_i. \tag{2.8}$$

In this model, the dependent variable is the household saving rate, which is defined as the ratio of household disposable income minus household consumption to household disposable income.

The explanatory variable of interest $\boldsymbol{D}_{\mathrm{incG}_i}$ is a vector of dummy variables for income quintile that take a value of one if the household's income belongs to specific income quintile and zero if the ith household's income is not in this quintile. These dummy variables capture the different types of income class as discussed in the simple theoretical model in Section 2.3. The regression model in Equation (2.8) also includes some control variables that capture household characteristics and household head's characteristics. These independent variables are used to control for other saving motives in the existing literature. The regression errors are denoted by ϵ.

The regression model (2.8) is estimated by running the mean and the median cross-sectional regression. In each case, we include dummies for all income quintiles except for the first one. The critical parameters of interest are the coefficients of the income quintiles. Each estimated β for a given income quintile captures, all else equal, the average excess saving rate for households in that quintile relative to households in the last income quintile.

The measurement

The variables used in our analysis include household consumption, household income, household demographic variables (household size, young dependent ratio, old dependent ratio), precautionary-type variables (employed status, employed type, hukou, health status, health insurance, pension, housing), competitive-type variables (number of boys and girls, age of children), and a set of household head characteristics (age, gender, married status, ccp member, years of schooling). The detailed definition of each variable is shown in panel (a) of Table A.3. Panel (b) - (d) of Table A.3 shows the summary statistics of these variables in the full sample.

Endogeneity

One problem in the regression (2.8) is the correlation between `current income` and the error term. According to Friedman (1957), one's consumption at a point in time does not only depend on the current income, but also on the permanent income, the expected long-term average income. To solve the endogeneity issue of current income, we adopt two approaches. First, since the previous related literature has typically found that the association between current income and permanent income will become close to one between one's mid-thirties and forties (see Haider and Solon, 2006, Böhlmark and Lindquist, 2006, and Grawe, 2006), we do the regression on a subsample which is restricted to include those households whose head's age is between 30 and 45. Obviously, this approach will suffer a dramatic decrease in sample size. Second, we deal with the endogeneity issue by constructing the measure of permanent income following the most applicable approach in Fuchs-Schündeln and Schündeln (2005) and Bhalla (1980). Specifically, we use an average of the current income and the recent past incomes as a proxy for the measure of permanent income, and then re-group households by using quintile based on the measure of permanent income.

Robustness check

To examine to what extent the analysis results are robust, we conduct several robustness checks. First, using the definition of non-entrepreneurs in Gentry and Hubbard (2000) (the value of business income for a household is less than $5,000), we restrict our samples to non-entrepreneurs so that we can test if the saving behavior of entrepreneurs drives the main results.[7] Second, we consider if the relationship between income and saving rate is consistent for the older ages population, by restricting our sample to households with household head's age above sixty. Third, rather than define income quintile by household income, we use per capita household income to regroup households as income quintile dummies to check the robustness of the estimates. Finally, we investigate whether or not the main results are robust by using an alternative definition of household saving rate introduced in Chamon and Prasad (2010) and Wei and Zhang (2011).

2.4.2 Liquidity constraints and saving rate

In Section 2.2, we present data evidence that across three sources data sets, there are more households may face a liquidity constraint for the bottom 20 percent of income group than that for the top 20 percent of income group, and within each income group, the saving rate for the constrained households tend to be higher than that for the unconstrained counterpart in each income bracket. In this subsection, we formally estimate the probability gap of facing liquidity constraints between income quintiles and the effect of the liquidity constraints on the household saving rates.

First, we run a probit regression to estimate the difference in probability of facing liquidity constraints between income quintiles

$$\Pr(\texttt{LC}_i = 1) = \Phi(\alpha + \boldsymbol{\beta} \cdot \boldsymbol{D}_{\text{incG}_i} + \boldsymbol{\gamma} \cdot \boldsymbol{X}_i), \tag{2.9}$$

[7] In the literature, Quadrini (1999, 2000), Gentry and Hubbard (2000), and Hurst and Lusardi (2004) have emphasized that the high-income entrepreneurs plays an important role in wealth accumulation and thus in savings.

where $\texttt{LC}_i$ is a dummy variable, which takes a value of one if household i face a liquidity constraint and zero if the household does not face a liquidity constraint. We use two ways to measure whether or not household i is facing a liquidity constraint, that is, the variable $\texttt{LC}_i = 1$. One is the definition in Zeldes (1989a), which states that a household is liquidity constrained if the total value of financial assets is less than two months permanent income. Another is directly from our CHFS questionnaire, which asks respondent "Does your family have any credit cards, excluding inactivated cards?" $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. The explanatory variable $\boldsymbol{D}_{\mathrm{incG}_i}$ and control variables $\mathbf{X}_i$ are the same as Equation (2.8). When do the regression, the last income quintile is omitted so that the coefficients of interest $\boldsymbol{\beta}$ are used to measure the difference in probability of facing a liquidity constraint relative to the last income quintile. We also use three-year moving average income as a proxy to permanent income to solve for the endogeneity problem in the probit regression.

Next, we use a Difference-in-Difference (DID) method to estimate the effect of the liquidity constraints on the household saving rates. Specifically, we estimate the following model

$$\begin{aligned} \texttt{saving rate}_{it} = \alpha + \beta \cdot \texttt{credit}_{it} \cdot D_{it} + \gamma \cdot D_{it} + \rho \cdot \texttt{credit}_{it} \\ + \delta \cdot \texttt{household income}_{it} + \boldsymbol{\mu} \cdot \boldsymbol{X}_{it} + \epsilon_{it}, \quad t = 1, 2, \end{aligned} \tag{2.10}$$

where $\texttt{credit}_{it}$ is a dummy variable which takes a value of one if household i is credit constrained in the first period but unconstrained in the second period and zero otherwise. D_{it} is a time dummy variable that takes a value of one if $t = 2$ and zero if $t = 1$. $\texttt{household income}$ is household's total disposal income, and $\boldsymbol{X}$ includes other household and household head's characteristics that are the same as previous regression equations. ϵ refers to regression errors. The key coefficient of interest is β, which measures the average "treatment" effect of credit unconstrained on the household saving rate.

The "common trend" assumption is required to be held for identifying β in DID approach. That is, in the presence of financial constrained, households without financial constrained would have experienced changes in saving rate similar to those with financial constrained. We address the validity of this assumption by using the t-test of all the controlled characteristics of the treatment and comparison group since we only have one-year panel sample before the treated year. After the control variables t-test for these two groups, all the indicators on the leading year are not statistically different between treated and comparison group; therefore, it provides support for the validity of the identifying assumption.

2.4.3 Income inequality and saving rate

In order to identify the effects of income inequality on household saving rate at aggregate level, we estimate the following regression model

$$\texttt{county saving rate}_i = \alpha + \beta \cdot \texttt{Gini}_i + \boldsymbol{\gamma} \cdot \boldsymbol{X}_i + \epsilon_i, \tag{2.11}$$

where the dependent variable is `county saving rate`, which is defined as the ratio of the sum of total household savings in the same county to the sum of total household disposable income in the same county. `Gini` is the Gini coefficient at county-level, and $\boldsymbol{X}$ contains other county characteristics. ϵ refers to regression errors. The key coefficient of interest is β, which measures the average effect of income inequality on the aggregate saving rate at county-level.

We focus on the Gini coefficient as the primary measure for income inequality, and use other measures, including the income ratio of the top 20 percent of households to the bottom 20 percent of households as a robustness check. Control variables in $\boldsymbol{X}$ include other county demographics such as *log* of county per capita income, county level young dependent ratio, and county level old dependent ratio, and etc.

2.4.4 Marginal propensity to consume (MPC)

The old idea that the marginal propensity to consume out of current income is diminishing, that is, consumption function is concave in current income, can be dating back to the discussion in Keynes (2016), which writes "…not only is the marginal propensity to consume is weaker in a wealthy community, but, …" in part II of Chapter 3, and "But with the growth of wealth and the diminishing marginal propensity to consume, …" in part V of Chapter 23. On the theoretical side, a formal analytical explanation for the intuition does not appear until Carroll and Kimball (1996).[8] On the empirical side, there is little recent literature that provides the micro empirical evidence that the marginal propensity to consume for the rich is lower than that for the poor. Lusardi (1996) estimates the changes in household consumption response to the changes in transitory income using two panel data sets and provides evidence of the concavity of the consumption function, and Souleles (1999) examines the response of household consumption to income tax funds and finds that the response is smaller for rich households.[9]

In this subesection, rather than estimating the changes in consumption response to the changes in income, we estimate directly the marginal propensity to consume out of current income following Paxson (1992). Specifically, we estimate the following equation

$$\texttt{consumption}_i = \alpha + \beta \cdot \texttt{transitory income}_i + \gamma \cdot \texttt{permanent income}_i + \boldsymbol{\delta} \cdot \boldsymbol{X}_i + \epsilon_i, \tag{2.12}$$

where `consumption` is household total consumption, `transitory income` is the measure of household temporary income in current period, which equals to the difference between `current income` and `permanent income`, `permanent income` refers to the household's ex-

[8]Carroll and Kimball (1996) show that a sufficient condition for the concavity of consumption function, in most of the cases, is that introducing income uncertainty into the utility maximization problem. Before them, Zeldes (1989b) uses numerical methods to show adding labor income uncertainty can make consumption function concave, and Kimball (1990) explains the increase in the slope of the consumption function.

[9]There is an older literature focusing on the test of the hypothesis of permanent income, which also finds the concavity evidence, e.g.

pected long-term average income, and $\boldsymbol{X}$ summarizes household characteristics and household head's characteristics. The key coefficient of interest is β, which measures, by definition, the marginal propensity to consume out of transitory income.

For the measure permanent income, as in the previous subsection, we use the moving average of three years income as a proxy for the permanent income. Equation (2.12) is estimated by running five separate cross-sectional regressions, with each one focusing on an income quintile sample.

2.5 Empirical Results

In this section, we present our main results to answer four empirical questions: (1) whether rich households tend to save more? (2) whether poor households are more likely to face liquidity constraints, and the liquidity constraint makes the household saving rate higher? (3) whether income inequality, at the county-level, has a positive effect on aggregate household saving rate? (4) whether the marginal propensity to consume for poor households is higher?

2.5.1 Income and saving rate

The empirical model in Equation (2.8) is estimated using the CHFS 2015, CFPS 2014, and CHIP 2013 data. The coefficient of interest is the parameter of the income quintiles $\boldsymbol{\beta}$, which measures the additional saving rate for each income quintile relative to the first one when controlling for the effects of all other factors that may also affect the household saving rate. The estimates in Table A.4 are estimated by median regression, and the standard errors for the coefficients are achieved in parentheses by bootstrapping based on 500 replications.

Saving rate and current income

Panel (a) of Table A.4 presents our estimation results with the first two columns showing the estimated effects for CHFS 2015 Urban, the next two columns for CFPS 2014 Urban, and the last two columns for CHIP 2013 Urban. Odd columns show estimates without controlling for the variable `employ_typ`, while the estimates in even columns controlling for it.

Column 1 and column 2 of the panel (a) suggest that the household saving rate increases dramatically with measured current income in the CHFS. The increments in the median household saving rate range from 30 percent in the second lowest income quintile to above 70 percent in the highest, and they are strictly increasing from the lowest income quintile to the highest. All the differences in these columns are statistically significant at 1 percent significant level. We also report the estimates for other factors that may affect the household saving rate. Among demographic-type factors, one increase in household size (`hh_size`) would decrease household saving rate by 2 percent, and a 1 percent increase in the old-dependent ratio (`ODratio`) would increase 0.07–0.10 percent saving rate. Both estimates are significant. These results are consistent with the existing demographic explanations about Chinese household saving rate. In precautionary-type variables, a household with urban hukou would decrease saving rate by 2 percent in column 1, although it is not significant when controlling for employ type `employ_typ` in column 2. The private burden of possible expenditures on health and housing would have a positive effect on the household saving rate in column 1, which is also consistent with the explanation focusing on precautionary motives.

Column 3 and column 4 shows results from similar regressions using the CFPS data. The estimates of the coefficient between the household saving rate and current income are smaller than in the CFPS. Nevertheless, we still see the estimated the differences in median saving rate rising significantly from 25 percent for households in the bottom quintile to over 50 percent of households in the top quintile. The qualitative effects of other factors such as household size, hukou, health, and housing on the saving rate are robust, although the magnitude is different.

The remaining columns of the table show the relationship between the household saving rate and current income in the CHIP data. As in the CHFS and the CFPS, the change in the saving rate strictly increases as income quintile moves up. For the second lowest-income households, the estimated median saving rate is 7–8 percent higher than the lowest-income, and for the highest income quintile, it is 25 percent higher than the lowest. Although the estimates are much lower than the comparable numbers from the CHFS and the CHIP, the result is not surprising: the variation in household income is much smaller in that the CHIP covers a more substantial proportion of households working in the state-own enterprise (SOE).

Endogeneity: saving rate and permanent income

We now adopt two approaches described in Subsection 2.4.1 to investigate the relationship between the household saving rate and permanent income. We first do the regression on a subsample which is restricted to include those households whose head's age is between 30 and 45. Obviously, this approach will suffer a dramatic decrease in sample size. Then, we use an average of the current income and the recent past incomes as a proxy for the measure of permanent income and re-group households by using quintile based on the measure of permanent income. The results are presented in panel (b) of Table A.4, with the first two columns showing the estimated results for CHFS, the next two columns for CFPS, and the last two columns for CHIP.

The odd columns of the table show that when subsample regression is used to consider the endogeneity issue. The estimated change in the saving rate increases consistently with income level for all three data sets. Indeed, the difference in the saving rate is significantly positive for every quintile at 1 percent significant level, range from 35 percent to 82 percent in the CHFS, 26 percent to 62 percent in the CFPS, and 8 percent to 23 percent in the CHIP. The estimated gradients of the coefficients are similar to (and in some cases slightly larger than) to those in panel (a), the relationship between the saving rate and the measured current income.

Our next approach is to use a three-year moving average current income as a measure of the permanent income. For the CHFS, we do have three years income data surveyed in 2010, 2012, and 2014. For the CFPS, we also have income data surveyed in 2009, 2011, and 2013. Although the CHIP data cannot keep track of households over time because it does not have a panel dimension, it contains information about previous incomes, and thus we can still calculate a three-year average income. The results are reported in the even columns of the table. This procedure also yields a strong relationship between the saving rate and the permanent income. For the CHFS, the estimated differences in the saving rate range from 5 percent for the second lowest-income quintile to 19 percent for the highest-income quintile. Except for the estimated differences for the second lowest-income quintile, the CFPS also shows a highly significant correlation, with the range the range from 14 percent for the third income quintile to 17 percent for the top income quintile. For the CHIP, the estimated changes in the saving rate are all significant, with the range from 8 percent for the bottom 20 percent of households to 23 percent for the top 20 percent. In all cases, we again see the saving rate strictly increases with the predicted permanent income. What's more, the magnitudes of the saving rate with respect to income are quite close across the three data sets, but the estimates are much smaller than those in panel (a) and the odd columns. This result suggests that much of the effects of transitory income is eliminated when simply using a three-year average as a proxy to permanent income.

Robustness checks

We now turn to show several tests to check the robustness of the main results. We first extend the analysis to explore the extent to which dropping all entrepreneurs with business income is greater than $5,000 (Gentry and Hubbard, 2000) affects the results. Next, we present the results where we restrict the sample to households at older ages (above 60) from the analysis. Finally, we investigate whether the effects are robust by using an alternative definition of household saving rate introduced in Chamon and Prasad (2010) and Wei and Zhang (2011) and by constructing quintile dummies using per capita income, respectively.

In panel (c) of Table A.4, we present the estimates based only on non-entrepreneurs and older households. Odd columns in the table continue to show a highly significant positive correlation between the median household saving rate and the income quintile, with the range of the differences in saving rate from 44 percent for the second lowest-income quintile to 91 percent to the highest in the CHFS, from 23 percent to 60 percent in the CFPS, and from 9 percent to 24 percent in the CHIP. When considering only the older households, the estimated differences in the even columns are still significantly positive and strictly increasing, with the gradients much higher for the CHFS and the CFPS and similar to the previous results for the CHIP. The estimated differences rise from above 70 percent for the second income quintile to above 140 percent for the fifth in both CHFS and CFPS, whereas from 8 percent to 27 percent in the CHIP. These even higher estimates suggest no evidence that at the older age, high-income households dissave at a faster rate than low-income households.

Panel (d) of the table shows the results using an alternative definition of saving rate (in the odd columns) and alternative income quintile (in the even columns). Again, the results show that there is a strong positive association between the saving rate and income in all three data sets, and the estimates strictly income with income level. The CHFS has the largest estimated coefficients in both odd columns and even columns, with the range from 33 percent for the second lowest-income quintile to 121 percent for the highest-income, while the chip's estimated coefficients are smallest in both odd columns and even columns, with the range from 8 percent for the second quintile to 25 percent for the fifth quintile.

The validity of the theoretical model

Finally, we present the empirical counterpart of the assumption in Section 2.3 and examine the validity of the theoretical model. Since we do have data on previous period wealth, there are only results for the CHFS and CFPS in panel (e) of Table A.4, with first three columns are results for the CHFS, and the last three are for the CFPS.

The first column is estimated from the similar regression to Equation (2.8) with restricting the sample to households having data on previous period wealth in the CHFS. The estimated differences in the saving rate are all significantly positive and strictly increasing. We report the estimated differences in the ratio of previous wealth to current income for income quintiles in column 2. The results show that the changes in the ratio strictly decrease as income quintile moves up. The estimated ratio is six times lower than the bottom 20 percent for the second lowest-income quintile, ten times lower for the third income quintile, 12 times lower for the second highest, and 15 times lower for the highest. This suggests that the assumption is realistic and reasonable. After controlling for the wealth-income ratio, in column 3 of the table, the effect of the ratio on saving rate is significantly negative. Besides, we see again highly significant and strictly increasing estimated differences in saving rate for income quintile. The smaller coefficients for the income quintiles along with a significant negative coefficient for the ratio implies that the previous wealth-current income ratio may be a channel in explaining why the rich tend to save more. As in the CHFS, similar patterns can be found in the CFPS, and they are shown in column 4–6.

We summarize the results presented so far: looking at all three data sets, although the estimates in magnitude of the increments in median household saving rate for different income quintiles relative to the bottom 20 percent differ, the pattern is generally the same —— as income quintile moves up, the difference in the saving rate between the higher income quintile and the lowest income quintile is strictly increasing, which implies that the rich do save more.

2.5.2 Liquidity constraints and saving rate

After carefully examining the relationship between the income distribution and household saving rate, in this subsection, we formally illustrate that the bottom 20 percent households are significantly more likely to face a liquidity constraint than the richer household and that liquidity constraint will lead to about 20 percent of household saving rate increases. We use two ways to measure whether household i is facing a liquidity constraint, that is, the variable $\texttt{LC}_i = 1$. For one measurement, we can use the financial liquidity constraint measure of Zeldes (1989a) in our three sources data sets. Zeldes (1989a) is the first paper using this financial constraint measure, "a household is liquidity constrained if the total value of financial assets is less than two months permanent income," and applying it into the PSID data. The paper finds that the consumption growth responds very strongly to lagged disposable income for the household with low wealth and also find that the similar estimated responses were sometimes statistically insignificant and smaller. He interprets this results as evidence that in favor of liquidity constraints and between 30 to 66 percent of households in PSID sample are liquidity constrained by this measurement and different definitions of "low wealth". For another measurement, we use it directly from our CHFS questionnaire, which asks respondent “E2002: Does your family have any credit cards, excluding inactivated cards?”. For the households who reply the question "Yes" as the answer will not face the liquidity liquidity constraint, and the counterpart will face the liquidity liquidity constraint, that is $\texttt{LC}_i = 1$, due to the household do not own an activated credit card. Since only the China Household Finance Survey ask the respondent question about the credit card information, we only use CHFS 2015 data to examine the relationship between the liquidity constraint and income distribution.

Liquidity constraints and current income

In this subsection, our dependent variable is the probability of $\texttt{LC}_i = 1$, whether household i is facing a liquidity constraint, and the explanatory variable of interest is also the income quintile dummy variables vector $\boldsymbol{D}_{\mathrm{incG}_i}$. We omit the highest income quintile for the reference in each regression and directly report the marginal effects of each explanatory variable in the results table for the explanation convenience. Both the results from using the household current and permanent income, we illustrate similar evidence suggest that financial constraint and borrowing constraints are important for the poor household in China which is consistent with the evidence of U.S. (Zeldes, 1989a).

First column of panel (a) and the odd columns of panel (b) of Table A.5 present our estimation results showing the estimated effects of the current income distribution on the first measurement of financial liquidity constraint. Column 1 of the panel (a) suggest that the probability of the household facing the binding financial constraint increases dramatically with measured current income in the CHFS. The increments in the probability of facing financial liquidity constraint range from 2 percent in the second highest income quintile, 5 percent in the third highest income quintile, 9 percent in the second lowest income quintile to 10 percent in the lowest income quintile all compared to the highest quintile of current income. Except for the coefficient of second highest income quintile, all the difference in this column is statically significant at 1 percent significant level. The poor are significantly more likely to face the liquidity constraint, and this relationship pattern is the same for CFPS and CHIP data. The odd columns of panel (b) of Table A.5 shows that the increments in probability of facing financial liquidity constraint range from 5 to 6 percent in the second highest income quintile to 23 to 13 percent in the lowest income quintile all compared to the highest quintile of current income for the CFPS and CHIP data respectively. Almost all the difference in this column are statically significant at 1 percent significant level. Therefore, the estimates pattern in magnitude of the increments in probability of facing the liquidity constraint using the current income quintile is generally the same: as income quintile moves down, the difference in the probability of facing the liquidity constraint between the higher income quintile and lowest income quintile is strictly increasing, which implies that the poor are more likely to face the financial liquidity constraint.

For the current income distribution on the second measurement of liquidity constraint, column 3 of the panel (a) present our estimation results showing the estimated effects. Column 3 of the panel (a) suggest that the probability of the household facing the binding liquidity constraint increases dramatically with measured current income in the CHFS. The increments in the probability of facing liquidity liquidity constraint range from 13 percent in the second highest income quintile, 18 percent in the third highest income quintile, 23 percent in the second lowest income quintile to 27 percent in the lowest income quintile all compared to the highest quintile of current income. All the difference in this column is also statically significant at 1 percent significant level. The poor are significantly more likely to face the binding liquidity constraint. The magnitude of the effects on liquidity constraint is much larger compared to the first financial measure using the CHFS data. The reason is that the credit card application in China has multiple criteria such as the stable income with good credit record or history, enrolled in the social security system and working job type. A household with "self-employed", "owning small private business" or "farmers" are all very difficult to apply for the credit card in China financial institution. So the variance of the second measurement variable is larger than the first one, the difference of facing the liquidity constraint from the financial institution is more important and severe for the poor household. Therefore, the difference in the probability of facing the liquidity constraint, measured as "without an activated credit card," is strictly increasing as income quintile moves down, which also implies that the poor are more likely to face the liquidity liquidity constraint.

Liquidity constraints and permanent income

These above estimates may be potentially problematic if there is a third factor that varies across the population and is driving the difference between the probability of facing the financial liquidity constraint and current income or if there exists reverse causality. For example, although the current income level of a household will lead to the liquidity constraint degree, facing the binding borrowing or financial liquidity constraint will also lead to the short-term property and total income reduction. Therefore, we also use the household permanent income to correct this endogeneity, and the permanent income is defined same as the above in three data sets.

Column 2 in the panel (a) of Table A.5 suggest that the probability of the household facing the binding financial constraint increases dramatically with permanent income defined same as the above in the CHFS. The increments of magnitude and significance in probability of facing financial constraint with the permanent income quintile is similar to the current income, range from 1 percent in the second highest income quintile, 4 percent in the third highest income quintile, 7 percent in the second lowest income quintile to 12 percent in the lowest income quintile all compared to the highest quintile of permanent income. The magnitude of this pattern is slightly larger for the second measurement of liquidity constraint column 4 of panel (a): from 7 percent in the second highest income quintile, 12 percent in the third highest income quintile, 16 percent in the second lowest income quintile to 17 percent in the lowest income quintile all compared to the highest quintile of permanent income. The magnitude of the effects on liquidity constraint is smaller compared to the current income quintile analysis using the CHFS data. All the differences in this column are statically significant at 1 percent significant level. Similarly, the pattern also holds or CFPS and CHIP data. The even columns of the panel (b) of Table A.5 also shows the increments effects range from 5 to 6 percent in the second highest income quintile to 20 to 15 percent in the lowest income quintile all compared to the highest quintile of permanent income for the CFPS and CHIP data respectively. Almost all the difference in this column are statically significant at 1 percent significant level. Therefore, the difference in the probability of facing the financial or borrowing constraint is strictly increasing as permanent income quintile moves down. Since the permanent income for the household can be treated as exogenous in the current financial or borrowing constraint situation, these results confirm our theoretical implication along with the data facts that the poor household are more likely to face the financial and borrowing liquidity constraint than the counterpart in China.

We also report the estimates for other factors that may affect the probability to face the financial or borrowing liquidity constraint both for the current income and permanent income specification. In demographic-type variables, 1 percent increase of the young-dependent ratio (`YDratio`) will decrease the probability of facing the liquidity constraint by 0.22 to 0.24 percent. Among precautionary-type factors, the registered residence status (`hukou`) change form the rural *hukou* to the non-rural *hukou* will decrease the probability of facing the liquidity constraint by 7 to 8 percent, which is consistent with the explanation that *hukou* restrictions system can depress private consumption demand of the migrant or the non-rural *hukou* household in the urban city. In addition, the household which has a poor health person or not being enrolled in public or private health insurance or pension insurance system will increase the probability of facing the liquidity constraint by 6 to 7 percent, 3 to 5 percent and 12 to 13 percent, respectively, taken the household social security into consideration. The estimated age-profile of the probability of facing the liquidity constraint is like hump-shaped, as the estimated coefficient of age (`age`) and age square ($\texttt{age}^2$) is significantly positive and significantly negative, respectively. A married household will be 4 to 5 percent significantly less likely to face the liquidity constraint due to the complete family structure and the China Communist Party membership of the household head will be 1 to 3 percent significantly less likely to face the liquidity constraint. Moreover, the household head with one more year of schooling will decrease the probability of facing the liquidity constraint about 2 percent. All the above-estimated coefficient of these other factors are statistically significant from zero and consistent with consistent with the explanation of previous literature.

Liquidity constraints and household saving rate

Similar to the Zeldes (1989a) as in the U.S., we next to issue that the liquidity constraint is important to understand the poor household consumption and saving behavior. Therefore, in this subsection, we identify the effect of liquidity constraint on the household saving rate in China. In fact, in the previous specifications on identifying the income distribution and saving rate, we control our liquidity constraint measure and find the significant negative effects if the household has the financial credit or an activated credit card; however, these estimates may be potentially problematic if there exists reverse causality. For example, the current income and saving level of a household will definitely affect the next period income and also affect the household financial and credit market behavior. Also, a third unobservable factor such as the risk and financial attitude that drives the difference between the household liquidity constraint and consumption behavior. Therefore, we use a Difference-in-Difference (DID) method to estimate the effect of the liquidity constraints on the household saving rates.

We only use the household that is credit constrained in 2013 as the whole sample from CHFS data and separates them into two groups: treatment group is the unconstrained household in the year 2015 and comparison group is the still constrained group in the year 2015. We use the Difference-in-Difference (DID) specification, and the variable of interest is the interaction term of treatment dummy and year dummy variable, which measures the average "treatment" effect of credit unconstrained on the household saving rate.

We use the t-test of all the controlled characteristics of the treatment and comparison group in the leading year to address the validity of the "common trend" assumption. AS the results, we provide support for the validity of this identifying assumption. Thus, according to the Difference-in-Difference (DID) specification, the key coefficient of interest is that before the interaction term of treatment dummy and year dummy variable. As the column 1 and 2 of Table A.6 shows, the estimated effects of credit unconstrained on the household saving rate is significantly negative by using the credit card measure. The difference of odd and even column is that the income control variable, for the odd ones we simply control for the household disposable income, and control for the logarithm of household disposable income for the even ones. Compared to the still credit constrained sample, the credit unconstrained sample will decrease the household saving rate by 11 to 27 percent, that is to say, the average "treatment" effect of credit unconstrained on the household saving rate is impressive, and credit constraint is an anchor to reduce the saving rate especially for poor households.

Columns 3 to 6 of Table A.6 show the estimated effects of credit unconstrained on the household saving rate is significantly negative by using the financial credit measure (Zeldes, 1989a) by using the CHFS and CFPS data. The most recent CHIP data sample of the year 2013 is in the year 2009, and it should be more problematic due to the longer time span. The Difference-in-Difference (DID) specification and the t-test for the two sample groups are also the same The magnitude and significance of the interaction term are similar for the financial constraint measures. Compared to the still financial credit constrained sample, the financial credit unconstrained sample will decrease the household saving rate by 21 to 26 percent and 24 to 26 percent for CHFS and CFPS data, respectively. The conspicuous effect of the borrowing and financially unconstrained on the household saving rate confirm our data facts and theoretical implication that the existence of the liquidity constraint leads to a significantly higher household saving rate and also expect the liquidity constraint lead to higher aggregate saving rate if we measure household sample as more aggregate level.

2.5.3 Income inequality and saving rate

Evidence across counties: cross-section regressions

We have seen that the household saving rate response to a move up in the current and permanent income quintile significantly positive. We address the research question what the general equilibrium effect of the aggregate household saving rate from a rise in the income inequality. We raised this by examining the calculated county-level data and indicators from CHFS 2015, CFPS 2014 and CHIP 2013 data sets for any association between local total saving rate and Gini coefficient. The three data sets cover 353 counties, 334 counties and 212 counties, respectively. The empirical exercise is valid for the causal relationship between the local total saving rate and inequality measure because the inequality across the county has no association with the county local saving rate after controlling for the location fixed effects. The income inequality indicators we use is the Gini coefficient and other measures such as coefficient of variation, Theil index, Mehran index, Piesch index, Kakwani index and the income ratio of the top 20 percent of households to the bottom 20 percent of households or relative mean deviation (Chu and Wen, 2017; De Maio, 2007). We perform the cross-sectional regression that links a county i's saving rate in the year 2013-2015 with the inequality index, controlling for location fixed effects and other factors. The variable we controlled maintain the previous specification as the (Schmidt-Hebbel and Serven, 2000) such as the local level young-dependent ratio (`YDratio`) and the old-dependent ratio (`ODratio`). To be precise, we report the results both controlling the county level young-dependent ratio (`YDratio`) and the old-dependent ratio (`ODratio`) or not to check the robustness of the effect. The location local saving rate and the inequality indexes, along with the young-dependent ratio (`YDratio`) and the old-dependent ratio (`ODratio`) are computed from CHFS 2015, CFPS 2014 and CHIP 2013 data sets. The saving rate of each county is defined as local total income minus consumption, divided by income. The inequality measure is defined as (De Maio, 2007) and local per-capita disposable income is defined as the county local total income divided by the local total population. We cluster the standard errors by province.

Income inequality and aggregate household saving rate

The odd column of Table A.7 report the regression results with only county per-capita income and Gini coefficient as the regressors, using the CHFS, CFPS and CHIP data set, respectively. The effect of income inequality on local saving rate is significantly positive at 5 percent level: a 1 percent increase in the Gini coefficient is associated with higher county saving rate by 0.18–0.20 percent points. The coefficient on local per-capita income is around 0.33 and statistically different from zero at the 1 percent level. In other words, CHFS 2015 data reveals that the county level saving rate tends to be higher in the county with more unbalanced income distribution. In any case, we note that similar household saving rate age-profile patterns relative to the prediction of the life cycle hypothesis are documented in Chamon and Prasad (2010) since we note that the share of young-age population and the old-age population has a positive significant coefficient. A 1 percent increase in the the old-dependent ratio (`ODratio`) or young-dependent ratio (`YDratio`) is associated with 0.35 to 0.6 percent higher county saving rate. These results may imply that that old-age households or household with children tend to save more than working-age household, however the significant association appears in the CHFS data set is not consistent for other two data sets. Columns 3 to 6 of Table A.7 show the estimated effects of Gini coefficient on local saving rate is not significant: a 1 percent increase in the Gini coefficient is associated with insignificant higher local saving rate by 0.13 and 0.02 percent points for CFPS and CHIP data, respectively. To save space, we do not report the results using other inequality measures, and some of the association between the income inequality and local saving rate are significantly positive at 5 to 10 percent level. To summarize, although the positive relationship between high-income inequality and a high county level saving rate is not robust and statistically significant, we can conclude that the increase in the current income inequality would make the local total household saving rate even higher.

2.5.4 Marginal propensity to consume (MPC)

Friedman's permanent income hypothesis (PIH) states that one's current consumption is determined not just only by the current income but also by the expected future income (permanent income). The hypothesis suggests that the changes in consumption are mainly driven by the changes in permanent income rather than the changes in current income, which implies that the marginal propensity to consume (MPC) out of permanent income would be greater than the MPC out of current income. To know how Chinese household would respond to the current income, we estimate Equation (2.12) by running five separate cross-sectional regressions, with each one focusing on one income quintile sample. Table A.8 presents the estimates of the MPC out of each type of income.

In panel (a) of Table A.8, for both types of income, the estimated MPCs are significantly positive in the CHFS. The estimated MPCs out of permanent income range from 223 RMB per 1000 RMB for the highest-income quintile households to 778 RMB per 1000 RMB for the lowest. We notice that the coefficients are decreasing with income classes except for the quintile 4. For the quintile 4, the coefficients are 541 RMB per 1000 RMB, which is not only greater than the quintile 5 but also than the quintile 3. The estimated MPCs out of current income share the similar pattern to the permanent income. The lowest-income quintile has the largest coefficient of 788 RMB per 1000 RMB, and the highest-income quintile has the smallest MPC with 178 RMB per 1000 RMB. Except for the quintile 4, the coefficients exhibit a decreasing pattern with as income quintiles move up. The estimated MPC out of current income for the quintile 4 is 507 RMB per 1000 RMB, which is larger than the quintile 3 and 5. These results indicate that the MPC out of both types of income for the bottom 20 percent households is much higher than the top 20 percent.

Panel (b) shows the results from similar regression using CFPS. The MPCs for both types of income are highly significant. The estimates of the MPCs out of current income range from 336 RMB per 1000 RMB for the quintile 5 to 927 RMB per 1000 RMB for the quintile 1. They display a decreasing pattern with income levels except for the quintile 2, whose estimated MPC is 361 RMB per 1000 RMB, but it is still larger than the quintile 5. For the MPC out of permanent income, excluding the quintile 2, the coefficients are still exhibiting a decreasing pattern with income classes. A little bit differences from the MPC out of current income is that the coefficient for the quintile 2 is 347 RMB per 1000 RMB, which is the smallest among the five quintiles. The MPC out of both types of income for the lowest-income quintile is again much higher than the highest-income quintile.

The results of estimation from CHIP are shown in panel (c) of the table. The estimated MPCs out of permanent income is 613 RMB per 1000 RMB for the bottom 20 percent households. It increases a little bit to 623 RMB per 1000 RMB for the second income quintile and then decreases steadily from 510 RMB per 1000 RMB for the third income quintile to 233 RBM per 1000 RMB for the top 20 percent households. All the numbers are significantly positive. For the estimated MPCs out of current income, the CHIP data exhibit a diminishing pattern as income quintiles move up, decreasing from 563 RMB per 1000 RMB for the bottom 20 percent households to 167 RMB per 1000 RMB for the top 20 percent households. Except for the coefficient for the top 20 percent households, all others are statistically significantly positive. Besides, the results in the CHIP exhibit the pattern implied by the permanent income hypothesis (PIH) that the coefficients for the permanent income higher than that for the current income.

In sum, although we do not see a diminishing MPC with income classes across three data sets, there is still a not surprising pattern that the MPC out of both types of income for the bottom 20 percent households are much higher than that for the top 20 percent households. The results are consistent with empirical evidence in the literature.

2.6 Conclusion

We show in this paper the role of income inequality interacting with liquidity constraints in explaining the high household saving rate in China. In a simple two-period model, households are heterogeneous in income and subjective discount factor, and whether the liquidity constraint is binding, consumption and saving rate are endogenously determined. The model generates several predictions consistent data facts: (1) the rich save more; (2) the proportion of constrained households for the poor is higher than that for the rich; (3) liquidity constraints would increase household saving rate. (4) when income inequality increases, the rich save even more, in the meanwhile, the poor would also save more due to the binding liquidity constraints, and thus the aggregate household saving rate would rise.

Using three sources of large, nationally representative household survey data sets, the China Household Finance Survey (CHFS), the China Family Panel Studies (CFPS), and the Chinese Household Income Project (CHIP), we provide direct empirical evidence implied by the theoretical model. We find that in China, (1) the top 20 percent permanent income households' saving rate is 19–23 percent significant higher than the bottom 20 percent households'. (2) the bottom 20 percent permanent income households are more likely to face a liquidity constraint, with a 12–20 percent significantly higher probability; (3) the existence of liquidity constraints would lead to a significant increase of more than 20 percent in the household saving rate; (4) income inequality would have a significant positive impact on the aggregate household saving rate ath the county level, with a 1 point on a scale of 100 measure increase in the Gini coefficient leading to an increase of 0.2 percent in the aggregate saving rate; (5) the estimated MPC for the top 20 percent households range from 200 to 400 RMB per 1000 RMB, while for the bottom 20 percent, the range from 600 to 900 RMB per 1000 RMB.

These findings would have significant policy implications. The Chinese government's policies on reducing the saving rate have not yet produced substantial results. If income inequality and liquidity constraints were the key reasons for the high aggregate household saving rate, the resulting policy would be drastically different. For example, it is appropriate for the Chinese government to design some income redistribution programs (such as EITC) to reduce income inequality or devote more resources to support the credit market development. An economic policy of tackling income inequality would lower the aggregate saving rate, thus becoming a policy of economic transition and growth.

3. INCENTIVES AND UNCERTAINTIES IN A+B PROCUREMENT CONTRACTS

3.1 Introduction

Public procurement, which is the purchase by governments and state-owned enterprises of goods, services, and works, constitutes a substantial proportion of GDP and has a direct and vital impact on the economy. For example, according to estimations drawing from National Accounts data, governments in OECD member countries spend on average 12.1 percent of their GDP on public procurement in 2013. In the United States, public-sector procurement accounts for over 10 percent of GDP (Krasnokutskaya and Seim, 2011). An innovative procurement mechanism widely used by state transportation agencies to select qualified contractors is called A+B procurement contracts.[1] The A+B procurement contract also referred as the Cost-Plus-Time contract, is awarded through a first-price, sealed-bid scoring auction that scores bidders on the two-dimensional bid of contract items: the quoted cost (A component) and the quoted completion time (B component). The project will be awarded to the bidder with the lowest score. Motivated by the practical prevalence of this procurement mechanism, this paper makes the first effort to identify and estimate a structural model of A+B procurement contracts with time incentives and construction uncertainty. Our structural model can be used to conduct social welfare analysis of the A+B mechanism and will shed some lights on the study of contract design in procurement industry.

Drawing on the score auction model of Che (1993) and Asker and Cantillon (2008), we incorporate time incentives/disincentive scheme and allow for a discrepancy between the bidding time and actual completion time by incorporating construction risks. The contracting game and the constructing practice proceed as follows. Before the bidding stage, the procurer will announce an estimated bundle of construction costs and working days, a selecting

[1]In the 1990s, the A+B mechanism was first introduced by the Department of Transportation (DOT) of California as an experiment for emergency-type projects because of the criticism that highway constructions took too much time, and has been extended to non-emergency type project since 2000. See the memorandum issued by the DOT of California (`http://www.dot.ca.gov/hq/oppd/design/m093002.pdf`).

rule for awarding the contract, and a provision for rewarding early completion and punishing late completion. These are common knowledge to all players. Next, upon this information being advertised before bidding, each contractor's will quote a sealed price-day bid. The bid depends on contractor's innate efficiency cost parameter, which is served as a private information and is drawn independently by nature. The contract will be awarded to the bidder who has the lowest score, which is calculated by the procurer's pre-announced rule.

In the construction stage, before the winning contractor's work, a cost shock is realized and observed to the contractor. The contractor then rationalizes the actual working days to maximize the profit. Due to the existence of the construction uncertainties, the actual working days may deviate from the bidding days. Because of such discrepancy, the A+B contracting mechanism may be neither *ex-ante* nor *ex-post* efficient, meaning that the A+B mechanism may not select the contractor who will generate the highest social welfare among all bidders and the winning contractor will not necessarily maximize the social welfare.

We show that the model primitives including the contractor's cost function, the contractor's private-type distribution, incentive and disincentive parameters can be nonparametrically identified from the bidding dataset and contracting dataset. The identification of model primitives can be established through the equilibrium conditions implied by the model, together with some functional restrictions on the cost function and the variation of agents' characteristics. Specifically, our identification argument takes several steps. First, we use the result in the influential work of Guerre, Perrigne, and Vuong (2000) to identify the pseudo-type in the theoretical model. Similar to Guerre, Perrigne, and Vuong (2000), who provide a general identification result on the bidders' private-type, we explore the one-to-one mapping between the bidding score and the pseudo-type implied by the theory and the number of bidders to back out each bidder's private-type. Second, we use the result in Torgovitsky (2015) to identify the one-to-one structural link between the pseudo-type and the actual private-type. Some mild restrictions on the contractor's cost function, the variation of contractors' characteristics and bidding days, and the normalization condition of unobserved heterogeneity are used to recover the pseudo-type function. Based on these two identified one-to-one mappings, we can identify the contractor's private-type distribution according to the result in Matzkin (2003). Third, we use the observed actual working days to identify incentive and disincentive parameters. We show that the cutoff values of uncertainty for deciding whether or not to complete the project on-time or early or delay are the same across private-types. Having identified all objectives above, the identification of contractor's cost function is established accordingly.

We apply our model to evaluate the social efficiency of A+B contracts in California's construction projects between 2003 and 2008. The empirical questions we would like to address are twofold. First, whether the contractors selected by the California Department of Transportation will generate the highest social welfare among all competitors. That is, whether it is possible that there would exist another contractor who would produce a higher level of social welfare if it would be selected. We call this *ex-ante* efficiency. Second, no matter which contractor would be selected, whether or not it would always lead to a maximum level of social welfare. We call this *ex-post* efficiency.

Specifically, we propose a three-step semiparametric method to estimate the parameters of the structural model, and then based on the estimates, we simulate the actual working days for other contractors if they would implement the project under the same exogenous shocks. We find that 66 percent of A+B contracts are *ex-ante* inefficient with a welfare loss of $1.4 million per contract. Besides, we calculate *ex-post* optimal social welfare for each contract, and find that 52 percent of the contracts are *ex-post* inefficient with a welfare loss of $3.5 million per contract. Second, we perform two alternative mechanisms, and find that the counterfactual experiments would increase significantly social welfare in both *ex-ante* and *ex-post*. Specifically, we find that the counterfactual A design with time incentive contracting will decrease the ex-ante inefficiency to 8.7 percent and increasing welfare by 2.558 million dollars. Regarding ex-post efficiency, although all contracts will be inefficient under A design, the average welfare loss is much smaller (0.289 million dollars). Furthermore, under the alternative lane rental policy, the ex-ante inefficiency will be reduced by 61.4 percent on average with an average welfare gain of 0.569 million dollars. For ex-post inefficiency, the lane rental policy performs much better, with 100 percent inefficiency reduction and welfare gain of 4.135 million dollars.

Related literature

This paper is related to three main bodies of literature. A wide array of theoretical models of regulation have been used to study procurement problem (see, e.g., Weitzman, 1974; McAfee and McMillan, 1987; Riordan and Sappington, 1987; Laffont and Tirole, 1987, 1993; Manelli and Vincent, 1995; Krishna, 2009). In the context of A+B mechanism, Che (1993) studies a two-dimensional scoring auction when private information is one-dimensional and analyzes optimal buying mechanism. Branco (1997) explores the impact of correlated bidder costs on the design of the multidimensional mechanism. Asker and Cantillon (2008) provide a systematic analysis of equilibrium behavior in scoring auctions under bidders' multidimensional private information and show that scoring auctions dominate several other commonly used mechanisms. Along the lines of Che (1993) and Asker and Cantillon (2008), we propose a stylized model of A+B bidding in the context of highway procurement in an environment where construction uncertainty exists, and contractors may have the incentive to deviate their bidding when time incentive scheme is introduced.

This paper also contributes to broad literature on the identification and estimation of structural models in auction and contract theory. Guerre, Perrigne, and Vuong (2000) show that the underlying distribution of bidders' private values in the first-price sealed-bid auctions within the independent private values (IPV) framework can be nonparametrically identified from observed bids and the number of actual bidders. An, Hu, and Shum (2010) develop a nonparametric procedure to recover the conditional distribution of the bids given the number of bidders and consider the identification and estimation problem when the number of actual bidders is unknown to econometrician, exploiting the results from recent literature on the models with misclassification error (see, e.g., Mahajan, 2006; Hu, 2008). To our best knowledge, there are very few studies on the rigorous econometric analysis of models related to contract theory. Some of the previous studies build their argument upon the one-to-one mapping between the characteristics of contract in the data and unobserved type of agents (see, e.g., d'Haultfoeuille, Février, et al., 2007; Aryal, Perrigne, and Quang, 2012; Perrigne and Vuong, 2011, 2012). Comparing with their work, we consider A+B incentive contracts which are competed via a first-price sealed-bid scoring auction and develops a quantitatively different argument of identification. To our best knowledge, our paper makes the first attempt to formally address the issue of identification in the scoring auction models, which is innovative and novel in the literature

Besides, our paper contributes to a growing, but still relatively scarce empirical literature on auctions with multidimensional attributes (see, e.g., Levin and Athey, 2001; Marion, 2007; Lewis and Bajari, 2011; Krasnokutskaya and Seim, 2011; Krasnokutskaya, 2011; Bajari, Houghton, and Tadelis, 2014). Lewis and Bajari (2011) use the same sources of data as ours to estimate the benefits to commuters from the acceleration of completion time and that the contractual benefit gain from expanding the use of A+B mechanism design to all highway construction projects. In comparison, our work differs from Lewis and Bajari (2011) in several fundamental aspects. First, in terms of the theoretical model, we take into account the cost uncertainties when modeling the bidding environment and characterize contractors' behavior. Specifically, we show that discrepancy between the quoted completion days and intended actual completion days can happen due to the presence of unanticipated cost shocks during the construction stage. Second, concerning empirical results, we conduct the empirical analysis of social welfare related to the A+B mechanism and demonstrate that A+B mechanism can be neither ex-ante nor ex-post efficient, which contradicts the welfare analysis result in Lewis and Bajari (2011) since they ignore the construction uncertainties.

Roadmap

The rest of this chapter is organized as follows. Section 3.2 presents our model of A+B procurement contracting with time incentives and construction uncertainties. In Section 3.3, we establish the main identiïňAcation results. Section 3.4 introduces the A+B mechanism background of CalTrans highway procurement contracts, and describes the data. A three-step semiparametric estimation procedure is discussed in Section 3.5. Section 3.6 reports the estimation results. In Section 3.7, we conduct counterfactual welfare analysis of the A+B mechanism. Section 3.8 concludes. The Appendix contains proofs, figures, tables, and other details.

3.2 Model

In this section we lay out a structural model of A+B contracting along the lines of scoring auction literature (see, e.g., Che, 1993; and Asker and Cantillon, 2008). In addition to extending the classical scoring auction model to a two-stage model, when agents are making bidding decisions, the structural model also includes both time incentive/disincentive mechanism and construction uncertainties in the execution of the contract. The structural model allows us to quantify the importance of incentives and uncertainties in bidding decisions and estimate policy counterfactuals. For a generic function $f(\cdot)$ with more than one argument, we denote $f_l(\cdot)$ its derivative with respect to the l-th argument. A random variable is denoted by uppercase letter while its realized values are denoted by lower case letters.

3.2.1 Setup

A buyer (or procurer) seeks to procure an indivisible good (e.g., a highway project) among $N \geq 2$ potential risk-neutral bidders (or contractors). Unlike the traditional first-price auction, the bidder needs to submit a bid combination of total cost $p^B \in \mathcal{P} \subset \mathbb{R}_+$ and working days $x^B \in \mathcal{X} \subset \mathbb{R}_+$ in the procurement auction. The contract then is awarded via a so-called "first-score" auction in the sense that the lowest scorer wins the contract. The score is calculated by a rule, $s : \mathcal{P} \times \mathcal{X} \mapsto s(\mathcal{P}, \mathcal{X})$, which is determined by the procurer and represents a continuous preference relation of the buyer over the bid combination (p^B, x^B). The winning cost-time combination becomes the contractual cost and working days.

Contractor's cost function

We assume that contractors have different abilities, which reflect the innate efficiency cost ("type", hereafter) to complete the construction project and each contractor knows her own type. The type is denoted as θ, which reflects contractors-specific private information of cost, such as their current managerial capacity, their expertise with working on a tight schedule, and their relationships with input suppliers or with subcontractors. The total cost function is given by:

$$\underbrace{TC}_{\text{total cost}} = \underbrace{(1+\varepsilon)C(x^A, \theta)}_{\text{construction cost}} + \underbrace{K(x^A, x^B, i, d),}_{\text{incentive cost}} \tag{3.1}$$

where we assume that the total cost function consists of two parts and is additively separable. The first part in Equation (3.1) is the bidder's actual construction cost. We assume that it has a multiplicative structure. That is, the actual construction cost for the contractor equals a deterministic cost $C(x^A, \theta)$ times a percentage deviation from the deterministic part of construction cost due to the construction uncertainty ε. Similar assumption on the cost function in the literature includes Krasnokutskaya (2011), Bajari, Houghton, and Tadelis (2014), and etc. The multiplicative structure in cost function is implicit in Krasnokutskaya (2011), where the bidder's cost realization is given by an auction common component times an individual cost component. In Bajari, Houghton, and Tadelis (2014), the authors assume the bidder's actual cost is a variant of the engineer's cost estimate. The second part in Equation (3.1) is the incentive cost that captures rewards and punishments scheme in the contract. The incentive costs depend on the relationship between the actual working days x^A and the bidding days x^B, and incentive parameters i and d. The specification of incentive costs K is as follows:

$$K(x^A, x^B, i, d) = \underbrace{\mathbb{1}(x^A < x^B) \cdot i \cdot (x^A - x^B)}_{\text{reward early completion}} + \underbrace{\mathbb{1}(x^A > x^B) \cdot d \cdot (x^A - x^B),}_{\text{punish delay completion}} \tag{3.2}$$

where $\mathbb{I}(\cdot)$ is an indicator function, $i \in \mathbb{R}_+$ and $d \in \mathbb{R}_+$ are daily cash bonus and daily cash punishment, respectively. Equation (3.2) implies that the contractor may face punishment if the project fails to be completed according to the contractual working days. Alternatively, the contractor may receive awards due to the early completion relative to the contractual working days.

Timing and decisions

The construction procurement usually takes place in three stages: First, at the beginning of the auction, the procurer announces three messages: (i) an engineer's estimated specification of the project, (p^E, x^E), which is the estimate of the project costs and the project length in working days respectively; (ii) a scoring rule $s : \mathcal{P} \times \mathcal{X} \mapsto s(\mathcal{P}, \mathcal{X})$ that associates a score to any potential contract and represents a continuous preference relation over the contractor's two-dimension bidding (p^B, x^B); (iii) an incentive/disincentive (I/D) scheme (i, d), which is the daily cash bonus for the early completion and the daily cash penalty for the delay completion, respectively.

Second, upon this information being advertised before bidding, each contractor draws the private-type $\theta \in \mathit{\Theta} \subset \mathbb{R}_+$ independently from a cumulative distribution function $F_\Theta(\cdot)$, with a density $f_\Theta(\cdot)$ on a support $[\underline{\theta}, \overline{\theta}]$. The contract then quotes a sealed price-days bid (p^B, x^B). The contract is awarded to the bidder that quotes the lowest score (a.k.a. the "winner").

Third, according to terms of the contract, the construction stage begins, and then the contractor receives payment when the project is completed. In the construction stage, the contractor may encounter various kinds of construction risks or construction uncertainties. The contractor may adjust implementation plan in response to them. We assume that all uncertainties are characterized by a percentage deviation from the costs and that they are realized at the beginning of the project to be carried out.[2] Figure B.1 illustrates the timing

[2]In fact, we assume that ε is a sufficient statistics that reflects all construction uncertainties in the implementation stage. This is an imperfect approximation, although, in the reality, the realization of construction uncertainties is a complex dynamic process because different kinds of uncertainties may occur at different

of events and decisions.

Remark. *The engineering's estimate (p^E, x^E) serves as a role of "reservation price"in standard auction models. Unlike the reservation price, however, (p^E, x^E) is announced by the procurer at the beginning and this is observed by all bidders. Neither $x^B > x^E$ nor $p^B > p^E$ can be acceptable by the procurer. Therefore, the procurer imposes an upper bound on the contractor's bid.*

3.2.2 Equilibrium

We now provide the details of contractors' behavior. We maintain the following restrictions on the cost function C and the scoring rule s throughout the paper. Notice that the engineer's estimate (p^E, x^E), the scoring rule $s(p^B, x^B)$, the incentive scheme (i, d), and type distribution $F_\Theta(\cdot)$ are common knowledge. This is an independent private values (IPV) framework.

Assumption 2. *The actual construction costs $(1+\varepsilon)C(x^A, \theta)$ for the private-type θ to complete the project in x^A days satisfy:*

(a) the uncertainty ε is independent and identically distributed according to a known distribution function $F_\varepsilon(\cdot)$ with a density $f_\varepsilon(\cdot)$ on its support $[-1, \infty)$ with the mean $\mathbb{E}(\varepsilon) = 0$.

(b) the deterministic cost function $C(\cdot, \theta)$ is strictly decreasing convex for every θ;

(c) $C(x^A, \cdot)$ is strictly increasing for every $x^A \in \mathbb{R}_+$, and the marginal cost $C_1(x^A, \cdot)$ is strictly decreasing for every $x^A \in \mathbb{R}_+$.

In the part (a) of the Assumption 2, we assume that the lower bound of the uncertainty is -1 to ensure non-negative actual cost; part (b) implies that the cost function is decreasing convex in actual working days x^A. To be specific, both the original construction cost, denoted as $C^o(e, \theta)$, and the actual working days $X^A(e)$ may be a function of expediting effort e, given a particular type θ. We assume that $C^o(e, \theta)$ and $x^A(e)$ are increasingly convex and decreasingly convex in e, respectively. Therefore, $C(x^A, \theta)$ is considered as a transformed cost

time points.

function with property of decreasingly convex in x^A.[3] Part (c) is standard in the procurement contract literature (see, e.g., Laffont and Tirole, 1993).

Assumption 3. *The scoring rule function S is given by:*

$$s(p^B, x^B) = p^B + c_u \cdot x^B, \tag{3.3}$$

where $c_u \in \mathbb{R}_+$ is the weight (user cost), calculating the time value in dollars.

The linear in price scoring rule in Assumption 3 is empirically relevant because it is widely used in many public procurement auctions of U.S. states' Department of Transportation (DoT), such as California, Delaware, Idaho, Massachusetts, Oregon, Texas, Utah, and Virginia, etc.[4]

When the project is completed and the payment from the procurer is received, the contractor's ex-post payoff π is given by:

$$\pi = p^B - TC = p^B - (1+\varepsilon)C(x^A, \theta) - K(x^A, x^B; i, d). \tag{3.4}$$

The contractor needs to make two decisions: (i) bidding cost and working days in the procurement auction and (ii) actual working days in the construction stage given winning the contract. Thus we solve the contractor's optimal bidding decisions on costs and working days by backward induction. First, if the contractor would win the contract, the winner chooses actual working days to maximize the payoff function in Equation (3.4), after knowing a realization of uncertainty ε at the beginning of the construction stage. We present an argument in Lemma 1 for the contractor's decision on actual working days.

[3] Lewis and Bajari (2011) assumed a U-shaped cost curve that seems to be a textbook long-run average cost curve, with the most efficient scale of construction at the engineer's estimate x^E.

[4] We admit that there are a variety of forms of scoring rules used in real-world public procurement. For example, many states in the U.S., such as Alaska, Colorado, Michigan, and North Carolina, use the price-over-quality ratio (PQR) rule to score the bidders; In addition, in some European countries, the scoring rule is the sum of the price and quality measurements, but the score is nonlinear in price. Here we restrict our attention to the quasi-linear score rule because of the data in hands.

Lemma 1. *Under Assumption 2 - 3, for any given bid* (p^B, x^B)*, incentive coefficients* (i, d)*, and the realization of private-type* θ *and uncertainty* ε*, the optimal completion time* $x^{A^*}(\cdot)$*, defined as* $x^{A^*} = \underset{x^A}{\operatorname{argmin}}\big\{(1+\varepsilon)C(x^A, \theta) + K(x^A, x^B; i, d)\big\}$*, can be characterized as follows:*

$$x^{A^*}(\theta, \varepsilon) = \begin{cases} x^d(\theta, \varepsilon) & \text{if } x^B \in [0, x^d\big) \quad \Leftrightarrow \quad \varepsilon \geq \varepsilon^d(x^B, \theta; d) \\ x^B & \text{if } x^B \in [x^d, x^i] \quad \Leftrightarrow \quad \varepsilon^i(x^B, \theta; i) \leq \varepsilon \leq \varepsilon^d(x^B, \theta; d) \\ x^i(\theta, \varepsilon) & \text{if } x^B \in \big(x^i, x^E] \quad \Leftrightarrow \quad \varepsilon \leq \varepsilon^i(x^B, \theta; i) \end{cases}$$

where $x^d(\theta, \varepsilon; C)$ *and* $x^i(\theta, \varepsilon; C)$ *satisfy* $-C_1(x^d, \theta, \varepsilon) = d$ *and* $-C_1(x^i, \theta, \varepsilon) = i$*, respectively;* ε^i *and* ε^d *satisfy* $-C_1(x^B, \theta, \varepsilon^i) = i$ *and* $-C_1(x^B, \theta, \varepsilon^d) = d$*, respectively.*

In this lemma, ε^i and ε^d denote the cutoff values for the cost shock ε. Specifically, if the realized value of ε is greater than ε^d (negative shock), then the optimal decision of the contractor is to delay the construction process and complete at x^d, which is greater than x^B. On the other hand, if $\varepsilon < \varepsilon^i$ (positive shock), the optimal decision is to complete early at x^i. Finally, if the cost shock is moderate, i.e., between ε^i and ε^d. The decision of the contractor is to stick to the original plan and complete exactly as the bidding time.

An important implication of Lemma 1 suggests that the optimal actual working days x^{A^*} may deviate from the bidding days x^B due to its dependence on the realization uncertainty ε. This is important because it may affect the contractor's bidder behavior. Figure B.2 illustrates the scenario of delay completion under negative construction shocks, meaning that the realized ϵ will increase the actual cost of completing the construction project.

Remark. *The construction uncertainty is important in our model since it provides the underlying source driving actual working days in the construction stage deviates (no matter what level of) bidding days in the bidding stage. However, without uncertainty, actually, working days solely depend on bidding days. That is, for some range of bidding days, actually working days will deviate bidding days, whereas for other range they are the same. We* *provide detail proof and illustration in Appendix.*

Next, we turn back to the contractors' bidding strategy in the competing stage. The contractor quotes a bid combination of costs p^B and working days x^A to do the following maximization:

$$\max_{p^B, x^B} \left\{ p^B - \mathbb{E}\min_{x^A} \Big[(1+\varepsilon)C(x^A, \theta) + K(x^A, x^B; i, d) \Big] \right\} \Pr\Big(\text{win} \;\Big|\; S = s\Big),$$

where s is the bidding score as in Equation (3.3) and $\Pr(\text{win}|S = s)$ is the probability for the bidder to win the auction given her bidding score. The expectation is taken with respect to the summary of construction uncertainties ε. Define the contractor's effective cost, or pseudo-type, which reflects the contractor's productive potential as

$$v(\theta) \equiv \min_{x^B} \Bigg\{ c_u x^B + \mathbb{E}\Big[(1+\varepsilon)C(x^A, \theta) + K(x^A, x^B; i, d) \Big] \Bigg\}. \tag{3.5}$$

Then following Che (1993) and Asker and Cantillon (2008), the contractor's optimization problem is equivalent to:

$$\max_{s} \big(s - v(\theta)\big) \Pr(\text{win} \mid S = s). \tag{3.6}$$

Let $F_V(\cdot)$ denote the CDF of the pseudo-type V and let $\underline{v}$ denote the lower bound for the support of V. Then the following proposition characterizes the unique symmetric pure strategy Bayesian Nash Equilibrium (psBNE) of the A+B bidding models.

Proposition 2. *Under Assumption 2, the model of A+B bidding has a unique symmetric psBNE* $\big(p^{B^*}(\theta; c_u, i, d), x^{B^*}(\theta; c_u, i, d)\big)$*:*

$$p^{B^*} = \mathbb{E}\Big[(1+\varepsilon)C(x^A, \theta) + K(x^A, x^B; i, d) \Big] - \int_{\underline{v}}^{v} \left[\frac{1 - F_V(\tilde{v})}{1 - F_V(v)} \right]^{N-1} d\tilde{v}, \tag{3.7}$$

$$x^{B^*} = \arg\min_{x^B} \Big\{ c_u x^B + \mathbb{E}\Big[(1+\varepsilon)C(x^A,\theta) + K(x^A, x^B; i, d)\Big]\Big\}; \tag{3.8}$$

Furthermore, if θ is scalar, then

$$p^{B^*} = \mathbb{E}\Big[(1+\varepsilon)C(x^A,\theta) + K(x^A, x^B; i, d)\Big] - \int_{\underline{\theta}}^{\theta} \mathbb{E}C_2(x^{A^*}, \theta, \varepsilon)\left[\frac{1-F_\Theta(\tilde{\theta})}{1-F_\Theta(\theta)}\right]^{N-1} d\tilde{\theta}. \tag{3.9}$$

$$\frac{\partial x^{B^*}}{\partial \theta}(\theta; c_u, i, d) > 0. \tag{3.10}$$

3.2.3 Discussion on social efficiency

To exam how the A+B mechanism affects the social welfare, we focus on two dimensions of social efficiency: (i) ex-ante efficiency and (ii) ex-post efficiency. Ex-ante efficiency means that the contract design always picks the right contractor in the sense that the winning contractor would generate the highest social welfare in equilibrium than that of others if they would perform the construction. Ex-post efficiency implies that no matter which contractor would win the contract, the winner always maximizes the social welfare. Let $SW \equiv V_c - (1+\varepsilon)C(x^A,\theta) - c_u x^A$ denote the ex-post realized social welfare, where V_c is the total value of the construction project, and $(1+\varepsilon)C(x^A,\theta) + c_u x^A$ is the total social costs (TSC) in which $c_u x^A$ is the cost due to the externalities of the construction.[5] Formally, the ex-ante efficiency and the ex-post efficiency are defined as follows:

Definition 1 (Ex-ante efficiency). *A contract design is **ex-ante efficient** if $s_i < \min_{j\neq i} s_j$ implies that $SW_i \geq \max_{j\neq i} SW_j$.*

[5]This specification is similar to the one in Lewis and Bajari (2011) where they claim that the linear structure in the working days, with a constant user cost as the coefficient, seems to be the right approximation although it is easy to be extended to the more complicated one.

Definition 2 (Ex-post efficiency). *A contract design is **ex-post efficient** if x^A maximizes SW for all type $\theta \in [\underline{\theta}, \overline{\theta}]$, i.e., x^A satisfies $-(1+\varepsilon)C_1(x^A, \theta) = c_u$.*

Figure B.4 illustrates that the A+B mechanism may be neither ex-ante efficient nor ex-post efficient when there is a cost shock to the cost function, e.g., an unexpected weather condition that happens during the construction stage. Consider two bidders, 1 and 2, with different private-types, θ_1 and θ_2 respectively, and $\theta_1 < \theta_2$. The theoretical model implies that the pseudo-type is a strictly increasing transformation of the private-type, and standard results from the auction literature imply that the contract will be awarded to the bidder with lowest pseudo-type. Thus bidder one will win the contract. As illustrated in Figure B.2, under a negative shock to the cost function, the bidder 1's best response to it may be to delay the completion at x_1^d, thereby the total social cost will be $c_u x_1^d + C(x_1^d, \theta_1)$ as shown in panel (1) of Figure B.4. However, if the bidder two would be awarded the contract and under the negative shock, the total social cost would be $c_u x_2^b + C(x_2^d, \theta_2)$, which is smaller than that of the bidder 1. This may be because that the bidder two can have much smaller private costs than that of bidder one, even though the working days conducted by bidder two would be longer than that of bidder 1. Thus, the A+B mechanism may not pick the most socially-efficient contractor from the ex-ante perspective.

Panel (2) of Figure B.4 shows that under the same negative shock to the contractor one, the A+B mechanism may not generate the highest social welfare. According to the definition of social welfare, the social optimal completion days should be $x_1^{c_u}$, at which the contractor internalizes the social costs and aligns the private interests with social interests. Therefore, as long as the actual working days deviate from $x_1^{c_u}$, due to the convexity of cost function in working days, the total social cost will be not be minimized, and thus the social welfare is not optimal.

3.3 Identification

In this section we show how the model primitives, denoted as $\mathcal{M} \equiv \left[C(\cdot,\cdot), F_\Theta(\cdot), i, d\right]$, can be identified when the data report the realized bidding costs p^B, the bidding working days x^B, the engineering's estimation of working days x^E, the actual working days x^A, and a vector of exogenous variables $\boldsymbol{z} \subset \mathbb{R}^D$ that summarizes bidders and contracts characteristics. The vector $\boldsymbol{z}$, for example in our empirical application of California highway procurement practice, can include firm capacity, location, distance and a binary variable indicating whether the contract is federally funded or not, etc. All the model primitives may depend on $\boldsymbol{z}$ or its sub-vectors. We suppress $\boldsymbol{z}$ whenever there is no ambiguity since our identification argument will be conditional on $\boldsymbol{z}$. We assume that the data observed is rationalized from the model primitives $\mathcal{M}$ and that the equilibrium conditions presented in the preceding section are satisfied.

Our identification strategy takes several steps. First, following a standard argument from Guerre, Perrigne, and Vuong (2000), we identify the pseudo-type $v(\theta)$ from the number of bidders in the procurement auctions and the distribution of bidding scores. Second, we recover the structural link between the (observed) bidding days and the distribution of the pseudo-type through an instrument variable, which is critical to the identification of the distribution of the contractor's private-type. Combining the identified distribution of pseudo-type and the identified structural link, we can recover the distribution of the private-type. Third, by exploiting the equilibrium conditions, the identification of incentive/disincentive parameters can be achieved. Finally, with the identification of model primitives above, we identify the marginal cost function through an exclusion restriction, which exploiting the variations in the quantiles of the cost and taking into account the fact that quantiles of the private-type distribution remain the same. We thus can identify the cost function up to a constant.

3.3.1 Identification of the pseudo-type's distribution

The first step of identification is to identify the pseudo-type v for each bidder. Following the results in Guerre, Perrigne, and Vuong (2000), we recover the value of pseudo-type, which is denoted as v, by exploring the equilibrium bidding strategy and the distribution of bidding scores. Specifically, the symmetric monotone pure strategy equilibrium in optimization problem (3.6) is obtained by solving the first-order differential equation in $s(\cdot)$:

$$s'(v) = (N-1)(s(v)-v)\frac{f_V(v)}{1-F_V(v)} \tag{3.11}$$

with boundary condition $s(\underline{v}) = 0$. By introducing the distribution of bidding score $F_S(s)$ and its density $f_S(s)$, and substituting $F_S(s) = \Pr(s(V) \leq s) = \Pr(V \leq s^{-1}(s)) = F_V(s^{-1}(s)) = F_V(v)$ and $f_S(s) = f_V(v)/S'(v)$ into (3.11), we get

$$v = s - \frac{1}{N-1}\frac{1-F_S(s)}{f_S(s)}. \tag{3.12}$$

Hence the pseudo-type in the symmetric monotone psBNE is identified.

Lemma 2. *Under Assumption 2 - 3, contractors' pseudo-type $v(\theta)$ defined in Equation (3.5) is nonparametrically identified.*

3.3.2 Identification of the private-type's distribution

We now turn to the nonparametric identification of the distribution of private-type F_Θ. Recall the definition of pseudo-type v, and denote

$$g(x^{B^*}, \theta) \equiv c_u x^{B^*} + \mathbb{E}[(1+\varepsilon)C(x^{A^*}, \theta) + K(x^{A^*}, x^{B^*}; i, d)],$$

where x^{B^*} is the equilibrium bidding days, x^{A^*} is the best response to the uncertainty, and recall that the expectation is taken with respect to the uncertainty ε. Then we have

$$v = g^*(x^{B^*}, \theta). \tag{3.13}$$

For notational simplicity, in the following discussion we suppress the optimal bidding strategy index B^* in (3.13) and denote $g(\cdot,\cdot)$ by the true function form when there is no ambiguity. Notice that the specification in (3.13) is nonseparable (not additively separable) in the latent private-type, θ, which captures unobserved heterogeneity in the effect of x on v.

In addition, x is endogenous explanatory variable because x is obtained as the equilibrium outcome, which is chosen by the contractor corresponding to θ (see, e.g., optimal bidding strategy). To identify $g^*(\cdot, \cdot)$, the following assumptions need to be formalized:

Assumption 4. *Let $\mathcal{G}$ denote the collection of admissible outcome functions on the support $\mathcal{X} \times \Theta$. If $g, \widetilde{g} \in \mathcal{G}$ are distinct, then there does not exist a strictly increasing function f such that $g(x, \theta) = \widetilde{g}(x, f(\theta))$ for all $(x, \theta) \in \mathcal{X} \times \Theta$.*

Assumption 4 is a normalization condition for point identification of function g^*. Matzkin (2003) showed that some normalization of unobserved heterogeneity is necessary for nonparametric identification. Specifically, she considers an nonseparable model $Y = m(X, \varepsilon)$, where X is exogenous, and m is strictly increasing in ε. Lemma 1 in Matzkin (2003) established that if there exists a strictly increasing transformation of ε, say $\tilde{\varepsilon}$, then the model cannot be identified. Thus, some normalization conditions are proposed to achieve identification purpose. See Matzkin (2003) for some specifications.

Assumption 5. *There exists an unobserved variable η and observed instrument variable $W \in \mathcal{W}$ for X such that $X = h(W, \eta)$ and satisfies (a) $W \perp\!\!\!\perp (\theta, \eta)$. (b) $h(w, \cdot)$ is strictly increasing for every w. (c) $V|X = x, W = w$ and $X|W = w$ are (absolutely) continuously distributed for all x and w.*

As is mentioned in Torgovitsky (2015), Assumption 5 (a)-(b) are essentially the scalar heterogeneity assumption for the first stage estimation of X on W and is the key restriction in the nonseparable model 3.13. Both the assumption that W is independent of (θ, η) and the property that $h(w, \cdot)$ is strictly increasing are standard in the literature of identification of nonseparable models with endogenous regressors (see, e.g., Imbens and Newey, 2009; Torgovitsky, 2015; d'Haultfoeuille and Février, 2015).

The requirement of Assumption 5 can be interpreted using the following example: suppose the instrumental variable W is whether the contract is federally funded or not ($W = 1$ or 0, respectively). Then Assumption 5 implies that whether the contract is federally funded or not is independent with bidder's private-type θ, which is plausible since private-type contains unobserved information about bidder's characteristics. Furthermore, in practice it is likely that bidder's bidding decision can be affected by the funding source for the contract.

The intuition of the identification method can also be illustrated using this example. By identification assumptions, bidders with bidding days $X = x_1$ in the auctions with federally funded contract ($W = 1$) are unobservably identical (in terms of private-type θ) to bidders with bidding days $X = x_0$ in the auctions with state funded contract ($W = 0$) for two distinct bidding days x_1 and x_0, as long as these two groups of bidders have the same rank in terms of their respective X distributions, i.e., $F_{X|W}(x_1|1) = F_{X|W}(x_0|0)$. Since W has no effect on V, and the pesudo-type $V = v$ has been identified by Lemma 2, the differences in pseudo-types between these two groups of bidders must be caused solely by the changes in X from x_0 to x_1. Therefore the function g^* can be point-identified by exploring the variations generated by these two groups of bidders.

Proposition 3. *Suppose Assumption 2-5 hold. Then the function $g^* \in \mathcal{G}$ is identified on $(\mathcal{X}, \vartheta)$.*

Because the function $g^*(x, \cdot)$ is shown to be strictly increasing for every x, the mapping between the function g^* and the distribution of the observable variables $F_{V,X}$ and the conditionally cumulative distribution $F_{\Theta|X}$ is, for every x and θ,

$$F_{\Theta|X}(\theta) = F_{V|X}(g^*(x, \theta)).$$

This is because $F_{\Theta|X}(\theta) = \Pr(\Theta \leq \theta \mid X) = \Pr(g^*(X, \Theta) \leq g^*(x, \theta) \mid X) = \Pr(V \leq g^*(x, \theta) \mid X) = F_{V|X}(g^*(x, \theta))$. Since g has been identified in the Proposition 2, $F_{\Theta|X}(\cdot)$ is identified accordingly. Therefore, the distribution of private-type can be recovered

$$F_{\Theta}(\theta) = \int_{\mathcal{X}} F(x, \theta) dx = \int_{\mathcal{X}} F_{\Theta|X}(\theta) F_X(x) dx = \int_{\mathcal{X}} F_{V|X}(g^*(x, \theta)) F_X(x) dx. \tag{3.14}$$

3.3.3 Identification of the cost function and other primitives

We now present the identification of cost function $C(\cdot,\cdot)$, the daily incentive rate i, and the disincentive rate d.

First, we show that the cutoff values of uncertainty for deciding whether or not to complete the project on-time or early or delay are the same across private-types. To see this, recall that the economic model in Section 3.2 implies that the cutoff values should set at the level that makes marginal revenue equal to marginal cost, that is,

$$-(1+\varepsilon^{\rho})C_1(x^B,\theta)=\rho,\quad \rho\in\{i,d\}.$$

Taking derivative with respect to θ on the both sides, we have

$$\frac{-d\varepsilon^{\rho}}{d\theta}C_1(x^B,\theta)-(1+\varepsilon^{\rho})(C_{11}(x^B,\theta)\frac{dx^B}{d\theta}+C_{12}(x^B,\theta))=0.$$

Then we have $d\varepsilon^{\rho}/d\theta=0$. This is because $C_{11}(x^B,\theta)dx^B/d\theta+C_{12}(x^B,\theta)=0$, which is shown in Proposition 2 in the Appendix. The probability of early completion is

$$\Pr(X^A<X^B)=\Pr(\varepsilon<\varepsilon^i)=F_{\varepsilon}(\varepsilon^i),$$

and it is same across different private-types because of the fact that ε^i is independent of θ. Therefore, ε^i can be identified as

$$\varepsilon^i=F_{\varepsilon}^{-1}(\Pr(X^A<X^B)),\tag{3.15}$$

where the distribution of uncertainty ε is assumed to be known and the probability of early completion can be identified via the frequency of early completion contracts among total observations. Similarly, ε^d can be identified as

$$\varepsilon^d = F_\varepsilon^{-1}(1 - \Pr(X^A > X^B)). \tag{3.16}$$

Having identified the thresholds ε^i and ε^d, we now present the identification of the expediting cost function $C(\cdot,\cdot)$. The F.O.C of solving for x^{B^*} is given by

$$c_u + \int_{-1}^{\varepsilon^i} (-a) dF(\varepsilon) + C_1(x^B, \theta) \int_{\varepsilon^i}^{\varepsilon^d} (1+\varepsilon) dF(\varepsilon) + \int_{\varepsilon^d}^{\infty} (-b) dF(\varepsilon) = 0,$$

plug in the equations for determining the cutoff values $i = -(1+\varepsilon^i)C_1(x^B,\theta)$ and $d = -(1+\varepsilon^d)C_1(x^B,\theta)$ and solve for $C_1(x^B,\theta)$ as

$$C_1(x^B, \theta) = \kappa, \tag{3.17}$$

where

$$\kappa = -\frac{c_u}{(1+\varepsilon^i)F_\varepsilon(\varepsilon^i) + (1+\varepsilon^d)(1 - F_\varepsilon(\varepsilon^d)) + \int_{\varepsilon^i}^{\varepsilon^d} (1+\varepsilon) f_\varepsilon(\varepsilon) d\varepsilon}.$$

We can see that the right hand side of the equation above is known since c_u is observed data, and by Assumption 2, F_ε and f_ε are known. Also ε^i and ε^d are already identified in the previous steps. Hence κ is identified, and it is a constant. Therefore, i and d can be recovered as $i = -\kappa(1 + F_\varepsilon^{-1}(\Pr(X^A < X^B)))$ and $d = -\kappa(1 + F_\varepsilon^{-1}(1 - \Pr(X^A > X^B)))$ respectively.

Finally, we show how to identify cost function $C(\cdot,\cdot)$. Recall the assumption in part (c) of Assumption 2, $C_1(\cdot,\theta)$ is strictly convex, then (3.17) admits a unique function $x^B = x^B(\theta;\kappa)$ by the Implicit Function Theorem. Using the argument in the proof of the Proposition 1 that $x^B(\cdot)$ is strictly increasing, together with the identified distribution of private-type F_Θ and the known distribution of bidding days F_{X^B}, we can recover the functional form of $x^B(\cdot)$. Specifically, since $F_\Theta(\theta) = \Pr(\Theta \le \theta) = \Pr(X^B \le x^B(\theta;\kappa)) = F_{X^B}(x^B(\theta;\kappa))$, then $x^B(\cdot;\kappa))$

can be identified

$$x^B(\theta;\kappa) = F^{-1}_{X^B}(F_\Theta(\theta)) \tag{3.18}$$

where $F^{-1}_{X^B}(\cdot)$ is the inverse of the curriculum distribution function of bidding days. (3.17) implies that the marginal expediting cost function C_1 can be identified. Therefore, the expediting cost function can be identified up to a normalization.

We summarize the results of identification in the following theorem.

Theorem 1. *Suppose Assumption 2-5 hold. Then the model primitives* $\mathcal{M} \equiv \left[C(\cdot,\cdot), F_\Theta(\cdot), i, d\right]$ *are identified.*

3.3.4 Discussion on the constructive estimation

This section discusses estimation method based on the identification results in Section 3.3. The model primitives we need to estimate include the cost function $C(\cdot,\cdot)$ and incentive and disincentive scheme i and d. The estimation method is an application of the semiparametric minimum distance method proposed in Torgovitsky (2017). Specifically, we will parametrize $C(x^B,\theta)$ and (i,d) so that $g(x,\theta)$ can be rewritten as $g_{\gamma_0}(x,\theta)$, where the subscript γ_0 denotes the true value of the parameters in $C(\cdot,\cdot)$ and (i,d). Since contractor's pesudo type v is unobserved in the data, we can use equation (3.12) and the nonparametric method proposed in Guerre, Perrigne, and Vuong (2000) the obtain the estimated value $\hat{v}$. Specifically,

$$\hat{v} = s - \frac{1}{N-1}\frac{1-\hat{F}_S(s)}{\hat{f}_S(s)}, \tag{3.19}$$

where $\hat{F}_S(s)$ and $\hat{f}_S(s)$ denote the nonparametric (kernel or series) estimator for the CDF and PDF of the bidding score s. By the identification results in Torgovitsky (2015), we have

$$\gamma = \gamma_0 \Longleftrightarrow (F_{X|W}(\cdot),\theta) \perp\!\!\!\perp W \tag{3.20}$$

for all γ in the parameter space Γ, where $F_{X|W}(\cdot)$ is the conditional CDF of X on the instrumental variable W. Equation (3.20) implies that

$$\begin{aligned}
D_\gamma(t) \equiv& \Pr\left[F_{X|W}(x|w) \leq t_x, g_\gamma^{-1}(x, \hat{v}) \leq t_\theta, w \leq t_w\right] \\
&- \Pr\left[F_{X|W}(x|w) \leq t_x, g_\gamma^{-1}(x, \hat{v}) \leq t_\theta\right] \Pr(w \leq t_w) \\
=& \Pr\left[x \leq Q_{X|W}(t_x|w), \hat{v} \leq g_\gamma(x, t_\theta), w \leq t_w\right] \\
&- \Pr\left[x \leq Q_{X|W}(t_x|w), \hat{v} \leq g_\gamma(x, t_\theta)\right] \Pr(w \leq t_w) \\
=& 0
\end{aligned}$$

for every $t = (t_x, t_\theta, t_w) \in \mathcal{T} \equiv (0,1) \times \Theta \times \mathcal{W}$ if and only $\gamma = \gamma_0$. Note that $Q_{X|W}$ is the conditional quantile function of X given W. Let $\|\cdot\|_\mu$ denote the L_2-norm with respect to a probability measure μ with support containing $\mathcal{T}$. Then $\|D_\gamma\|_\mu = 0$ if and only if $\gamma = \gamma_0$. Therefore given some consistent estimator $\hat{D}_\gamma$ of D_γ, we can estimate γ_0 by minimizing $\|\hat{D}_\gamma\|_\mu$.

Let $\hat{Q}_{X|W}$ denote a consistent estimator for the conditional quantile function $Q_{X|W}$[6]. Then following Torgovitsky (2017), a feasible estimator of $D_\gamma(t)$ can be constructed as

$$\begin{aligned}
\hat{D}_\gamma(t) =& \frac{1}{n}\sum_{j=1}^{n} \mathbb{1}\left[x_j \leq \hat{Q}_{X|W}(t_x|w_j), \hat{v}_j \leq g_\gamma(x_j, t_\theta), w_j \leq t_w\right] \\
&- \left(\frac{1}{n}\sum_{j=1}^{n} \mathbb{1}\left[x_j \leq \hat{Q}_{X|W}(t_x|w_j), \hat{v}_j \leq g_\gamma(x_j, t_\theta)\right]\right) \left(\frac{1}{n}\sum_{j=1}^{n} \mathbb{1}\left[w_j \leq t_w\right]\right),
\end{aligned}$$

and $\hat{\gamma}$ can be defined as any $\gamma \in \Gamma$ such that

$$\hat{\gamma} = \operatorname*{argmin}_{\gamma \in \Gamma} \|\hat{D}_\gamma\|_\mu. \tag{3.21}$$

Consistency and asymptotic normality follows directly from the results in Torgovitsky (2017).

[6]In practice, $\hat{Q}_{X|W}$ can be obtained by using empirical conditional quantile function when $\mathcal{W}$ is a finite set, or by using kernel smoothing quantile regression if W is continuously distributed.

3.4 CalTrans Auctions: Background and Data

In this section, we apply our model to analyze the auctions of highway construction contracts awarded by the California Department of Transportation ("CalTrans", hereafter). CalTrans is a government department in the state of California that is responsible for the planning, construction, and maintenance of public transportation facilities such as highway, bridge, and railways. The innovative A+B contract design was first introduced by the CalTrans in the 1990s as an experiment for emergency type projects and has been extended to non-emergency type projects since 2000. At the beginning of the design of each contract, the engineer will estimate the project's cost and a target number of working days for project completion. A maximum number of lanes that can be closed at each phase of the project and their closure time will also be specified by design engineers, based on advice from traffic operation unit. Finally, CalTrans will make a decision as to whether a standard first-price procurement auction or A+B auction should be adopted during the bidding stage of the construct.

In the standard design, the bidders draw private costs for completing the project once informed of engineer estimates and quotes their prices in the standard design, and the contract will be awarded to the bidder who quotes the lowest price and should be completed within the engineer's days estimate. In the A+B design, the contract will be awarded according to a scoring rule, and the contractor must complete the contract within the number of days they bid; otherwise, penalties, which equal to the user cost in A+B contracts, will be charged for late completion.

We use the same source of data as Lewis and Bajari (2011). The data includes 3202 bids submitted by contractors in 708 procurement contracts awarded by the CalTrans between 2003 and 2008. Among these contracts, 424 bids conducted in the 80 contracts that are implemented by the A+B mechanism. These contracts include barrier construction, bridge repair or resurfacing, new lane and ramp construction, road rehabilitation, slope work and widening/realignment. We index the contracts by $j = 1, 2, \cdots, N$ and the contractors by

$k = 1, 2, \cdots, Nj$ in the jth contract. For each contract, the data reports initial specification, which includes estimated project cost and working days, and actual specification adopted (actual cost and working days). The data also reports the bids submitted by all participating contractors in each auction as well as several characteristics of the contractors. These include user cost, which is the weight on the days in the A+B scoring rule, the distance between each contractor's location and the working site for the project, number of bidders in each auction, each contractor's capacity, which is measured as the total values of all contracts held by a particular contractor during our sample period, two binary variables that indicates whether the contractor is located in California and whether the contract is federally funded or not, average annual daily traffic near the contract location and the fraction of the total number of lanes on the highway that may be closed during construction hours.

Table B.1 presents the summary statistics for our data. The estimated cost and completing time for a standard A+B contract is about \$ 21.9 million and 314 days. During the bidding stage of each contract, the average working days each bidder submits is 190.1 days while the average actual working days for each contract is 183.9 days. Among the 80 A+B contracts, only about 42.5 percent (34) will be completed exactly as the bidding days. Therefore more than 50 percent of A+B contracts will be completed either earlier or later than contractor's bidding days. Figure B.6 shows the histogram of the difference between bidding days and actual working days. This provides some empirical evidence that contractors may strategically deviate from the bidding days in the execution phases.

As we note in the introduction, our paper is motivated by a different set of empirical questions than that in Lewis and Bajari (2011). Lewis and Bajari (2011) used this data to estimate construction costs of the procurement contract, which is assumed to be deterministic after the realization of contractor's private-type. However, in reality, it is common for the contractor to face cost uncertainty during the construction stage. For example, unexpected bad weather condition may increase the project cost and delay completion time. Therefore, in contrast, the three primary goals of our empirical application are (a) to estimate the expediting cost function and test the restrictions on it imposed by theoretical model in section 3.2; (b) to evaluate the efficiency of A+B mechanism from both ex-ante and ex-post perspective: specifically, we would like to answer the questions that whether the social welfare produced by other contractors would be greater than that of winning contractor in the A+B bidding and that whether winning contract would maximize the social welfare no matter which contractor wins the contract; and (c) to access the welfare gains that would be achieved from counterfactual alternatives including change of incentive rule in the A+B bidding and change of selecting mechanism to traditional one that only A is considered to award the contracts.

From a modeling perspective, there is a significant qualitative difference between our approach and that of Lewis and Bajari (2011). Specifically, Lewis and Bajari (2011) maintained that no cost uncertainty would happen during the construction stage of the project and hence contractor has perfect foresight about the construction cost during the bidding stage. Thus the model in Lewis and Bajari (2011) cannot explain why bidding days may deviate from actual working days in the data. In comparison we consider the possible discrepancy between the quoted completion days and intended actual completion days due to incentive mechanism, and incorporate the effect of construction uncertainty on realized actual completion days and answer empirical and policy questions (a)-(c) above.

3.5 Econometric Implementation

Our estimation strategy takes three steps. First, following a similar procedure as in Lewis and Bajari (2014) we estimate the private-type θ by regressing normalized bidding days on bidder's characteristics and obtaining the residuals as $\hat{\theta}$; Second, we estimate the equilibrium pseudo-type v by employing a semiparametric technique as in Bajari, Houghton, and Tadelis (2014). Finally, the cost function of the contractor will be estimated by treating θ and v obtained from the previous steps as data in the dependent variable and applying the method of minimum distance. The idea is to construct a minimum distance objective function based on the equilibrium pseudo-type equation (3.5).

Recall that the identification argument in Section 3.3 is presented for the simple case with homogeneous contracts, conditional on given contractors' characteristics, and no structural observational errors. In comparison, we consider in the current section a general environment that allows rich heterogeneity among the contract and contractors. Acknowledging the limited sample size and to make estimation feasible, we now adopt a parametric specification of model primitives.

3.5.1 Estimation of the bidder's private-type

Following the theory in Section 3.2, contractors have latent private-type θ. In order to estimate contractor's cost function $C(\cdot)$, we need to first obtain estimated value for θ. We assume that θ is independently and identically distributed across contracts and contractors with $\mathcal{N}(0, \sigma_\theta^2)$,[7] and use a linear regression procedure to estimate θ and σ_θ.

Recall Proposition 2 indicates that bidding days is strictly increasing in private-type, therefore in the first stage, we estimate the private-type θ by regressing bidding days (normalized by engineers' estimates) on bidders' specific characteristics and treat residuals as the estimated private-types for bidders.

$$\frac{x_{jk}^B}{x_{jk}^E} = \boldsymbol{z_{jk}} \cdot \boldsymbol{\omega} + \theta_{jk}, \tag{3.22}$$

where $\boldsymbol{z_{jk}}$ is a vector contains bidder's characteristics that are known to CalTrans as well as econometricians. Such a specification is also motivated by the fact the bidding days of each contractor in the auction stage depends on the cost shock ε only through its expected value. Note that the linear specification assumption is not necessary but easy to implement and interpret due to the limitation of sample size in data. With sufficient data, a nonparametric approach can be used instead. Hence under the linear specification, the private-types can be obtained as the residuals in estimating (3.22). Furthermore, σ_θ can be estimated as the

[7] Lewis and Bajari (2011) also assume that the private-type relating to acceleration is normally distributed, i.i.d across contracts and contractors, and argue that this assumption would validate because this is not a dynamic model, even though it may seem to be strong due to the persistence of some contractor characteristics.

standard deviation of the residuals.

3.5.2 Estimation of the equilibrium pseudo-type

In the second stage, we estimate the equilibrium pseudo-type v and then treat them as data of the dependant variable. Given the sample size, a nonparametric approach (see, e.g., Guerre, Perrigne, and Vuong, 2000) is not feasible since it requires us to nonparametrically estimate the conditional CDF $F_{S|\boldsymbol{Z}}$ and conditional PDF $f_{S|\boldsymbol{Z}}$, and it is well known that nonparametric (kernel or series) estimation will suffer from the curse of dimensionality when the dimension of $\boldsymbol{Z}$ is large. Consequently, instead of the fully nonparametric approach, we adopt the semiparametric procedure in Bajari, Houghton, and Tadelis (2014). Specifically, we estimate the conditional distribution of contractors' bidding scores via the following linear regression

$$\widetilde{s}_{jk} = \boldsymbol{z_{jk}} \cdot \boldsymbol{\psi} + \zeta_{jk}, \tag{3.23}$$

where the dependant variable $\widetilde{s}_{jk}$ is the normalized bidding score $\frac{s_{jk}}{s_j^E}$, where

$$s_j^E \equiv p_j^E + c_{u_j} x_j^E$$

is the bidding score computed by using engineer's estimated bidding price and time. As before, the vector $\boldsymbol{z_{jk}}$ includes the contractors' characteristics, and the idiosyncratic error ζ_{jk} is independent of $\boldsymbol{z_{jk}}$. As is mentioned in Bajari, Houghton, and Tadelis (2014), such specification allows for heterogeneity in the structural error via the contract size s_j^E.

For each contract indexed by j, we estimate the coefficient $\hat{\boldsymbol{\psi}}$ and then use it to calculate the residual $\hat{\zeta_{jk}}$ for all contracts. By construction,

$$F_{S|\boldsymbol{Z}}(s_{jk}) = \Pr\left(\boldsymbol{z_{jk}} \cdot \boldsymbol{\psi} + \zeta_{jk} \leq \frac{s_{jk}}{s_j^E} \mid \boldsymbol{Z}\right) = \Pr\left(\zeta_{jk} \leq \frac{s_{jk}}{s_j^E} - \boldsymbol{z_{jk}} \cdot \boldsymbol{\psi} \mid \boldsymbol{Z}\right) = F_{\zeta}\left(\frac{s_{jk}}{s_j^E} - \boldsymbol{z_{jk}} \cdot \boldsymbol{\psi}\right),$$

where $F_{\zeta}(\cdot)$ is the curriculum density function of ζ_{jk} (we suppress the dependence of $F_{S|\boldsymbol{Z}}$ and $F_{\zeta}(\cdot)$ on N_j to simplify notation). The corresponding conditional density of bidding scores is

$$f_{S|\boldsymbol{Z}}(s_{jk}) = \frac{\partial}{\partial s_{jk}} F_\zeta\left(\frac{s_{jk}}{s_j^E} - \boldsymbol{z_{jk}} \cdot \boldsymbol{\psi}\right) = \frac{1}{s_j^E} f_\zeta\left(\frac{s_{jk}}{s_j^E} - \boldsymbol{z_{jk}} \cdot \boldsymbol{\psi}\right).$$

By plugging in the estimate $\hat{\boldsymbol{\psi}}$, and the empirical distribution and kernel density of $\hat{\zeta}_{ij}$ to the right hand side above, we can get the estimate $\hat{F}_{S|\boldsymbol{Z}}$ and $\hat{f}_{S|\boldsymbol{Z}}$ respectively. Then using equation (3.12), the equilibrium pseudo-type for contractor i in the project j is estimated as

$$\hat{v}_{jk} = s_{jk} - \frac{1}{N_j - 1} \frac{1 - \hat{F}_S(s_{jk})}{\hat{f}_S(s_{jk})}. \tag{3.24}$$

3.5.3 Estimation of the cost function and other parameters

Model primitives specification

We specify the following quadratic functional form of the deterministic expediting cost by taking into account the contracts and contractors' heterogeneity

$$C(x, \theta; x^E, \boldsymbol{z}; \alpha_1, \alpha_2, \boldsymbol{\beta}, \phi) = \alpha_1 (x - x^E)^2 + (\alpha_2 \theta + \boldsymbol{\beta} \cdot \bar{\boldsymbol{z}})(x - x^E) + \phi, \tag{3.25}$$

where x is the actual working days, x_{jk}^E is the engineering's estimates of days to work, $\bar{\boldsymbol{z}} \subseteq \boldsymbol{z}$ is a vector of contracts and contractors' characteristics, parameters are $\alpha_1, \alpha_2, \beta$ and ϕ, with $\alpha_1 > 0$, $\alpha_2 < 0$, $\phi > 0$, respectively. The vector $\bar{\boldsymbol{z}}$ essentially contains some contract-level variables that are known to the contractors at the time of their decisions. This specification is adopted to capture asymmetry among contractors, and satisfies the restriction in Assumption 2 since actual working days x should never exceed the estimated working days by engineer. Such a specification is also followed by most of the empirical studies on procurement contracts (see, e.g., Lewis and Bajari, 2014).

In reality, in addition to the engineer's estimate of project costs and project length, incentive and disincentive provision may vary across contracts because of the value of the contract and the degree of project urgency. To capture this feature, the daily incentive and disincentive rates are specified as $i = ac_u$ and $d = bc_u$ respectively since c_u in general will vary across different contracts.

Recall that in the identification argument presented in Section 2 we assume that the distribution of implement uncertainty is known to econometrician so that the model primitives can be recovered from data. Along with this, we assume that the uncertainty is independently and identically distributed across contracts, truncated from a normal distribution $\mathcal{N}(0, \sigma_\varepsilon^2)$ with a two-sided truncation $-1 < \varepsilon < 1$.[8] Let γ denote the vector of parameters in this model, then $\gamma = \{\alpha_1, \alpha_2, \boldsymbol{\beta}, \phi, a, b, \sigma_\varepsilon\}$.

Estimation approach

The main idea to estimate γ is to employ the equilibrium pseudo-type equation as a regression function. There are two reasons to do so. First, it is complicated to get a closed-form solution for the bidding days due to the parametrized specification above, so is for the bidding costs. In order to use both information about bidding, which is a relatively large sample in our application, the equilibrium pseudo-type is a proper choice because it contains the information about the bidding days and bidding cost; next, taking into account the computation speed of estimation, the equilibrium pseudo-type would reduce much time of estimation because it involves less numerical integration than that of the bidding equation for the project costs.

The main estimation equation is based on the equilibrium pseudo-type equation (3.5). The challenge to estimate using (3.5) is that the equilibrium pseudo-type v in the dependent variable and the private-type θ in the explanatory variables are not available. Therefore we replace them with the estimated values in the first and second steps and estimate γ by a minimum distance method. Specifically,

$$\hat{v} - c_u x^B = \mathbb{E}[(1+\varepsilon)C(x^{A^*}, \hat{\theta}) - \rho \cdot (x^{B^*} - x^{A^*})], \quad \rho \in \{i, d\}. \tag{3.26}$$

[8]Normal distribution of construction risk is widely used in quantitative risk analysis in highway construction management practice. See Guide to Risk Assessment and Allocation for Highway Construction Management issued by U.S. Department of Transportation Federal Highway Administration.

Let $\hat{M}_{jk} \equiv c_{u_j} x^B_{jk} + \mathbb{E}\big[(1+\varepsilon_j)C(x^A_{jk}, \hat{\theta}_{jk}) - \rho_j \cdot (x^B_{jk} - x^A_{jk})\big]$ be the estimated value for the right hand side of equation (3.26), and let $\hat{\gamma} \in \Gamma$ denote the estimated value of γ, then model $\hat{\gamma}$ can be estimated via

$$\hat{\gamma} = \arg\min_{\gamma \in \Gamma} \sum_{j=1}^{N} \sum_{k=1}^{N_j} (\hat{v}_{jk} - \hat{M}_{jk})^2 \tag{3.27}$$

By treating $\hat{\theta}$ and $\hat{v}$ as data in the sample, we adopt a standard bootstrap procedure to calculate the standard error of parameters in the deterministic expediting cost functions and the daily incentive/disincentive coefficients.

3.6 Results

3.6.1 Parameters

Table B.2 reports the regression estimates for the normalized bidding days in (3.22) under three nested specifications. Note that the variable *capdummy* is a dummy variable and equals to one if the capacity of the contractor is greater than \$50 million. In all specifications, the *capdummy* has a significant (at 10 percent) and positive marginal effect (-0.0564 on average across all three specifications) on the normalized bidding days. This can be interpreted as the evidence of economies of scale in the construction costs for contractors working on multiple contracts simultaneously. Furthermore, the number of bidders has a significant (at 1 percent) and negative marginal effect (-0.0133 on average) on the normalized bidding days. This may indicate that increased competition in the auction stage will force bidders to shorten the bidding time for completing the project. Besides the user cost in the specification (2) and (3) has statistically significant (at 5 percent) and negative impact on the bidding days. Finally, the relatively small R^2 in all three specifications (0.055 on average) means that the private-type θ plays a deterministic role in contractor's bidding time decision.

The second stage regression estimates for (3.23) under three similar specifications as in the first stage are shown in Table B.3. Similar to the first stage, *capdummy* and the number of bidders have significant (at 1 percent) and negative impacts on the normalized bidding score in all three specifications. The regression results also indicate that contractors located in California will tend to have smaller bidding scores. This may be because contractors within California are more familiar with the working conditions of the highway construction projects and hence are more efficient in conducting the works. Note that in the first specification the normalized distance between contractor's location and the working site also has a significant (at 5 percent) and negative impact (2696.6) on its bidding score. In the second stage, we first use a nonparametric method to estimate the distribution of the residuals $\hat{\zeta}$, and then derive the distribution and density function for bidding score s using the estimated distribution. The kernel density estimate for $\hat{\zeta}$ in specifications (1)-(3) are demonstrated in Figures B.7, note that we use Gaussian kernel as the smoothing function and the bandwidth is selected according to the rule of thumb. For comparison, we also include the density plot based on the normal density function.

Table B.4 shows the estimates of parameters for the structural model under specifications (1)-(3) of the first and second stage estimation results. From the results in all three specifications, we can see that estimated value of α_1, α_2 are significantly (at 1 percent) positive and negative respectively. These results are in accordance with the structural model and indicate that the cost function is convex in working days and decreasing in private-type. Furthermore, the values of the estimated coefficients of incentive/disincentive (0.214/7.738 on average) also conform to our model set-up. The estimation results provide strong evidence that the data can be rationalized by our model. Note that in all three specifications the distance between contractor's location and the working site, and whether the contract is federally funded or not will have significant negative effects on contractor's cost. These results are consistent with practical construction works. The estimated standard deviation of the uncertainty ε is also significant with a p-value less than 0.01.

To quantify the welfare analysis of the A+B mechanism, we plug in the structural estimates in Table B.4 to compute the ex-ante and ex-post welfare loss under A+B design of the procurement contract. From the discussion in Section 3.2.3, an A+B contract is ex-ante inefficient if the winner of the contract under the A+B mechanism is not the one that generates the highest social welfare, and the ex-ante welfare loss is defined as the difference between the social welfare induced by the winner and the highest social welfare induced by other bidders. Analogously the contract is ex-post inefficient if the winner of the contract does not maximize the social welfare (complete the contract in the way that would minimize the total cost), and the ex-post welfare loss is defined as the difference between the social welfare generated by the operator of the contract and the maximum social welfare that would have been generated if the contractor had minimized the total cost.

The results of welfare comparison are shown in Table B.5. In all three specifications, more than 60 percent of the 75 A+B contracts in our sample are ex-ante inefficient, with an average welfare loss of 1.426 million dollars. Besides, the results also demonstrate that more than 50 percent of the A+B contracts will be ex-post inefficient and result in a welfare loss equal to 3.46 million dollars on average. Figure B.8 provides a graphical illustration of the welfare analysis. Specifically, panel (1) of Figure B.8 shows the rank (based on the total cost) of the auction winner among all bidders in each of the 75 A+B contracts, and panel 2 shows the difference between the actual and optimal (first best) total cost for each contractor. Our results provide strong empirical evidence to support the prediction of the theoretical model, i.e., when facing implementation uncertainty, it is highly possible that the A+B mechanism can neither accurately select the contractor who will generate smallest social cost in the bidding stage nor provide incentive for the contractor to minimize social cost in the execution stage.

3.6.2 Model fit

In this section, we show that the model fits the actual bidding and working behavior quite well under our parameterization of the cost function. We examine fit in a number of ways. In Figure B.9, we show empirical CDFs of each contractor's bidding days in actual data (blue, solid) and those simulated from the structural model (red, dashed). This is intended as an informal check on the shape of the distribution. In Figure B.10, we also plot the actual completion time for each A+B contract in actual data (blue, solid) and those simulated from the structural model (red, dashed). From these two figures, we can see that the model does an excellent job in predicting each contractor's bidding behavior and actual working days of each A+B contract in all three specifications. To further analyze the goodness of fit for the structural model, we conduct the regression analysis, and the results are presented in Table B.6 and B.6b. Specifically, we regress bidding days and actual working days in data on their simulated values obtained from the structural model. The results indicate that the model fits the data quite well in the sense that the coefficients of simulated data are significant (at 1 percent) and close to unity, and the R^2 is relatively high (0.784 on average) under all three specifications.

3.7 Counterfactuals

In this section, we consider two counterfactual policy changes and provide welfare analysis for each of them based on the estimated cost function for contractors. In the first counterfactual, we consider what would happen if the incentive/disincentive scheme is changed into a linear incentive (lane rental) contract, where the contractor pays a penalty (set equal to user cost) each day from the beginning of the contract. The second is a time incentive contracting in A design with the incentive cost $K = -i \cdot (x^E - x^A)$. For comparison, we also simulate outcomes and calculate welfare for current policy, i.e., A+B mechanism. We first provide some detailed explanations for the two counterfactual policies below.

Linear incentive contracting in A+B design

Under this policy design, the contractor have to pay a fixed amount of daily penalty (rent) from the beginning of the construction stage. regardless of the completion time of the project. The daily penalty will be set to equal to the user cost. Therefore the during the bidding stage the bidder's optimization problem becomes:

$$\max_{p^B, x^B} \left\{ p^B - \mathbb{E}\min_{x^A} \left[(1+\varepsilon) C(x^A, \theta) + c_u \cdot x^A \right] \right\} \Pr(\text{win} \mid S = s). \tag{3.28}$$

Optimal actual working days x^{A^*} responding to realized uncertainty should equal marginal cost to the daily disincentive rate, that is:

$$(1+\varepsilon)C_1(x^{A^*},\theta) = -c_u. \tag{3.29}$$

Thus, the ex-post efficiency can be achieved as long as the procurer set this daily incentive rate as user cost, even though in this case B part would be ineffective, that is, optimal bidding strategy for working days x^{B^*} equals to 0, and the optimal bidding cost would be

$$p^{B^*} = \mathbb{E}\big[C(x^{A^*},\theta,\varepsilon) + c_u \cdot x^{A^*}\big] - \int_{\underline{\theta}}^{\theta} \mathbb{E}C_2(x^{A^*},\theta,\varepsilon)\big[\frac{1-F_\Theta(\tilde{\theta})}{1-F_\Theta(\theta)}\big]^{N-1} d\tilde{\theta}. \tag{3.30}$$

In addition, under current setting the pseudo-type of bidder becomes

$$v(\theta) = \mathbb{E}\Big[(1+\varepsilon)C(x^{A^*},\theta) + c_u \cdot x^{A^*}\Big]. \tag{3.31}$$

Since the A+B mechanism selects the most efficient (with the smallest pseudo-type) bidder, by the envelope theorem the winner of the contract would perform at the lowest social cost, which implies the A+B contracting under linear incentive is ex-ante efficient as well.

Time incentives contracting in A design

Under this policy, contractor will be rewarded for early completion of the project, with rewards equal to $i \cdot (x^E - x^A)$[9]. Then the bidder's optimization problem becomes:

$$\max_{p^B} \Big\{p^B - \mathbb{E}\min_{x^A}\big[(1+\varepsilon)C(x^A,\theta) - i \cdot (x^E - x^A)\big]\Big\}\Pr(\text{win} \mid S = s). \tag{3.32}$$

Following Lewis and Bajari (2011), we assume that the engineerâĂŹs estimate of working days x^E is presumably close to the minimum cost which is the most efficient scale of

[9]If $x^E < x^A$, $i \cdot (x^E - x^A)$ becomes negative and is equivalent to penalties for late completion

construction. Recall the assumption that cost function is strictly decreasing and convex in x^A that are smaller than the most efficient working days. Consequently, in this case, any actual working days that is beyond the engineer's estimate is not rational for any contractor given a realized uncertainty, because not only do they face an increasing cost but also a daily penalty. Thus, the rational working days should be no more than engineer's estimate. Due to the existing of a positive daily incentive rate for early completion, the contractor will rationally choose actual working days such that the bonus of one day earlier completion is the same as the extra cost, which means that the optimal actual working days x^{A^*} satisfies

$$(1+\varepsilon)C_1(x^{A^*}, \theta) = -i. \tag{3.33}$$

Therefore contrary to the lane rental policy, the ex-post efficiency can not be achieved because the daily incentive i for early completion is smaller than the user cost c_u. Besides contractor's optimal bidding strategy can be characterized by the equation below:

$$p^{B^*} = \mathbb{E}\big[C(x^{A^*}, \theta, \varepsilon) - i \cdot (x^E - x^{A^*})\big] - \int_{\underline{\theta}}^{\theta} \mathbb{E}C_2(x^{A^*}, \theta, \varepsilon)\Big[\frac{1 - F_\Theta(\tilde{\theta})}{1 - F_\Theta(\theta)}\Big]^{N-1} d\tilde{\theta}. \tag{3.34}$$

However ex-ante efficiency can be guaranteed because under this policy design the bidder's pesudotype becomes

$$v(\theta) = \mathbb{E}\big[(1+\varepsilon)C(x^{A^*}, \theta) - i \cdot (x^E - x^{A^*})\big]. \tag{3.35}$$

By Assumption 2, the marginal cost $C_1(x^{A^*}, \theta)$ is strictly decreasing in x^{A^*} and θ, consequently based on (3.33), it is easy to verify that (3.35) is strictly decreasing in θ. Therefore the most efficient bidder will win the contract and the total social costs generated by that bidder should also be the smallest among all bidders[10].

[10]This is because the total social costs under x^{A^*} is also strictly decreasing in private-type θ.

Counterfactual analysis

To conduct counterfactual analysis, we simulate outcomes under the A+B policy and two counterfactual policies by sampling from the estimated distribution of θ and ϵ. Specifically in each iteration, we first randomly draw bidder's private-type from the estimated distribution of θ, and then follow the auction rules of each policy design to determine the contract winner by computing the bidding price (and days) for each bidder. Actual working days of the contractor will be calculated based on the realized uncertainty, which is sampled from the estimated distribution of ϵ. Finally, we conduct the ex-ante and ex-post welfare analyses by using a similar method as in Section 3.6.1 for all three policy designs

The results of welfare analysis are presented in Table B.7. We can see that changing the incentive scheme has a fairly big impact on inefficiency percentage and average welfare loss. The current A+B policy can lead to a large percent of ex-ante (81.5 percent on average) and ex-post inefficiency (100 percent) and average welfare loss of 3.556 (ex-ante) and 4.135 (ex-post) million dollars per contract. Under the alternative lane rental policy, the ex-ante inefficiency will be reduced by 61.4 percent on average with an average welfare gain of 0.569 million dollars. For ex-post inefficiency, the lane rental policy performs much better, with 100 percent inefficiency reduction and welfare gain of 4.135 million dollars. The A design with time incentive contracting also performs better than the A+B policy by decreasing the ex-ante inefficiency to 8.7 percent and increasing welfare by 2.558 million dollars. Regarding ex-post efficiency, although all contracts will be inefficient under A design, the average welfare loss is much smaller (0.289 million dollars) than the A+B policy.

3.8 Conclusion

This paper studies A+B procurement contracts in the context of highway projects construction. We set up a structural model that features by time incentives/disincentives, externalities, and construction risks. We explain why contractors often do not complete the projects on time. This discrepancy may make the A+B mechanism neither ex-ante efficient nor ex-post efficient. We show that the model components (the marginal expediting cost function, the distribution of private-type for contractors, and the incentive/disincentive daily rate) are all identified from the contract level and bid level data. We apply the model to analyze the data on the Caltrans auctions of highway procurement contracts. Our estimates provide substantial evidence that considering the existence of implement uncertainty in the structural analysis of bidding data leads to significant inefficiency.

4. SUMMARY

This dissertation applies alternative empirical methods in economics to study a "macro-phenomenon" — the "Chinese saving puzzle" and a "micro-mechanism" — the allocation of procurement contracts.

In the first paper, we investigate the role of income inequality interacting with liquidity constraints in explaining the high household saving rate in China. In a simple two-period model, households are heterogeneous in income and subjective discount factor, and whether the liquidity constraint is binding, consumption and saving rate are endogenously determined. The model generates several predictions consistent data facts: (1) the rich save more; (2) the proportion of constrained households for the poor is higher than that for the rich; (3) liquidity constraints would increase household saving rate. (4) when income inequality increases, the rich save even more, in the meanwhile, the poor would also save more due to the binding liquidity constraints, and thus the aggregate household saving rate would rise.

Using three sources of large, nationally representative household survey data sets, the China Household Finance Survey (CHFS), the China Family Panel Studies (CFPS), and the Chinese Household Income Project (CHIP), we provide direct empirical evidence implied by the theoretical model. We find that in China, (1) the top 20 percent permanent income households' saving rate is 19–23 percent significant higher than the bottom 20 percent households'. (2) the bottom 20 percent permanent income households are more likely to face a borrowing constraint, with a 12–20 percent significant higher probability; (3) the existence of liquidity constraints would lead to a significant increase of more than 20 percent in the household saving rate; (4) income inequality would have a significant positive impact on the aggregate household saving rate at the county level, with a 1 point on a scale of 100 measure increase in the Gini coefficient leading to an increase of 0.2 percent in the aggregate saving rate; (5) the estimated MPC for the top 20 percent households range from 200 to 400 RMB per 1000 RMB, while for the bottom 20 percent households, the range from 600 to 900 RMB per 1000 RMB.

These findings would have significant policy implications. The Chinese government's policies on reducing the saving rate have not yet produced substantial results. If income inequality and liquidity constraints were the key reasons for the high aggregate household saving rate, the resulting policy would be drastically different. For example, it is appropriate for the Chinese government to design some income redistribution programs (such as EITC) to reduce income inequality or devote more resources to support the credit market development. An economic policy of tackling income inequality would lower the aggregate saving rate, thus becoming a policy of economic transition and growth.

In the second essay, we study the A+B procurement contracts in the context of highway projects construction. We set up a structural model that features by time incentives/disincentives, externalities, and construction risks. We explain why contractors often do not complete the projects on time. This discrepancy may make the A+B mechanism neither ex-ante efficient nor ex-post efficient. We show that the model components (the marginal expediting cost function, the distribution of private type for contractors, and the incentive/disincentive daily rate) are all identified from the contract level and bid level data. We apply the model to analyze the data on the Caltrans auctions of highway procurement contracts. Our estimates provide substantial evidence that considering the existence of implement uncertainty in the structural analysis of bidding data leads to significant inefficiency.

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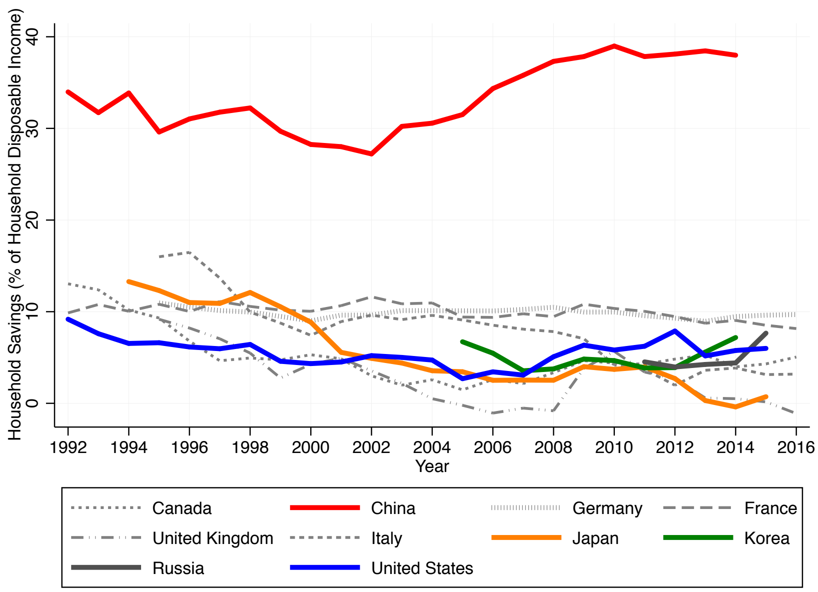
APPENDIX A

INCOME INEQUALITY, LIQUIDITY CONSTRAINTS, AND CHINA'S HOUSEHOLD SAVING RATE

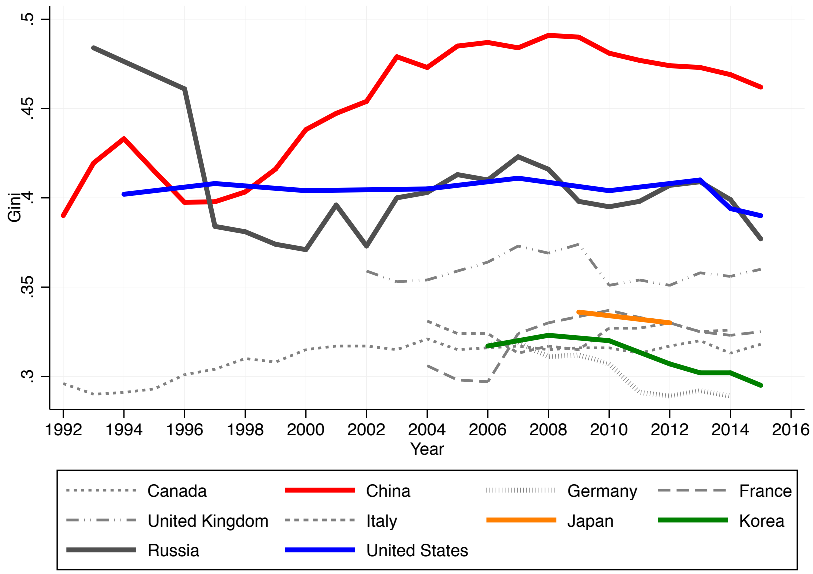
A.1 Figures

Figure A.1: International comparison



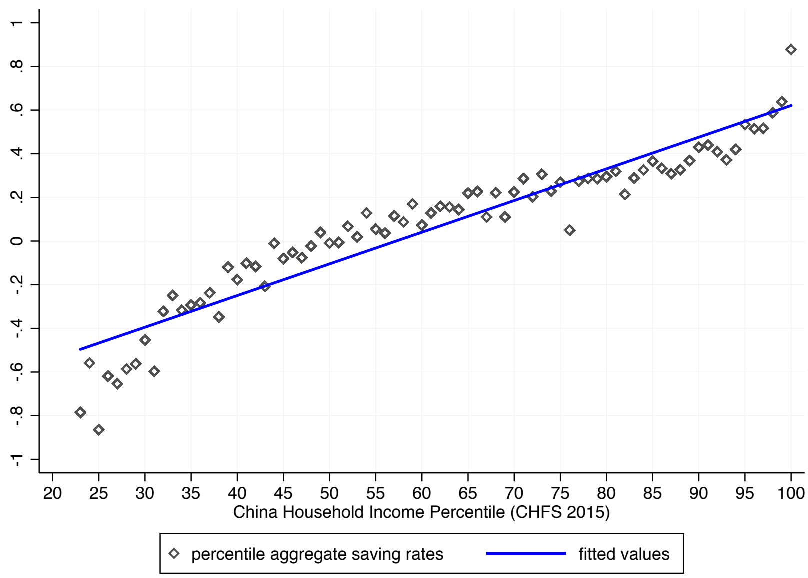
(1) Saving rate comparison across countries

Figure A.1: International comparison continued

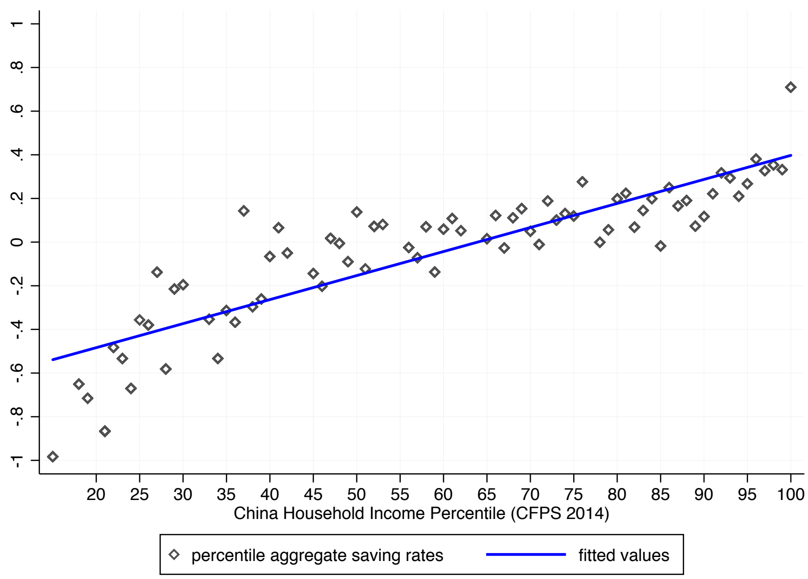


(2) Gini coefficient across countries

Figure A.2: China's household saving rate by income class

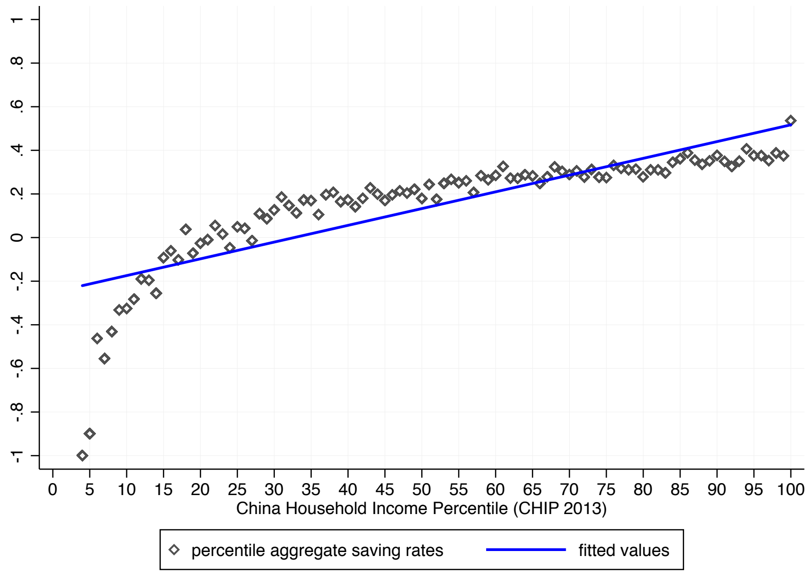


(1) CHFS 2015



(2) CFPS 2014

Figure A.2: China's household saving rate by income class continued



(3) CHIP 2013

Figure A.3: China's household saving rate and Gini coefficient

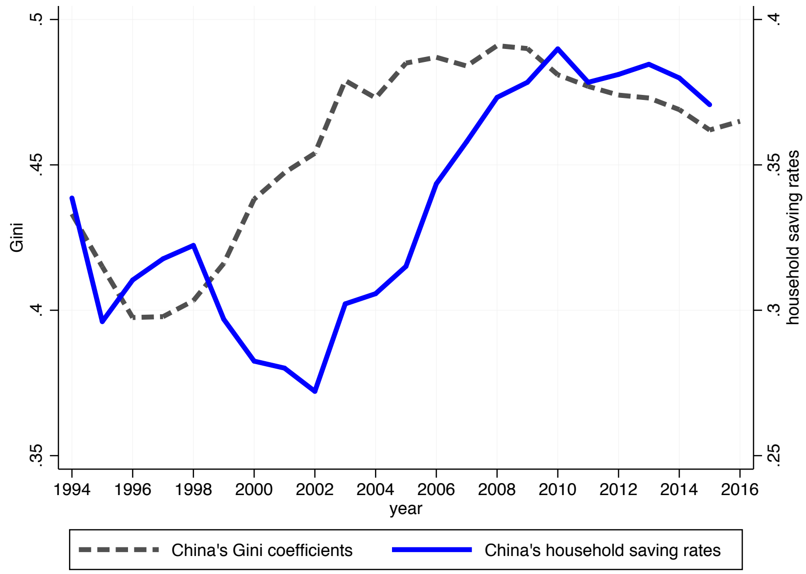
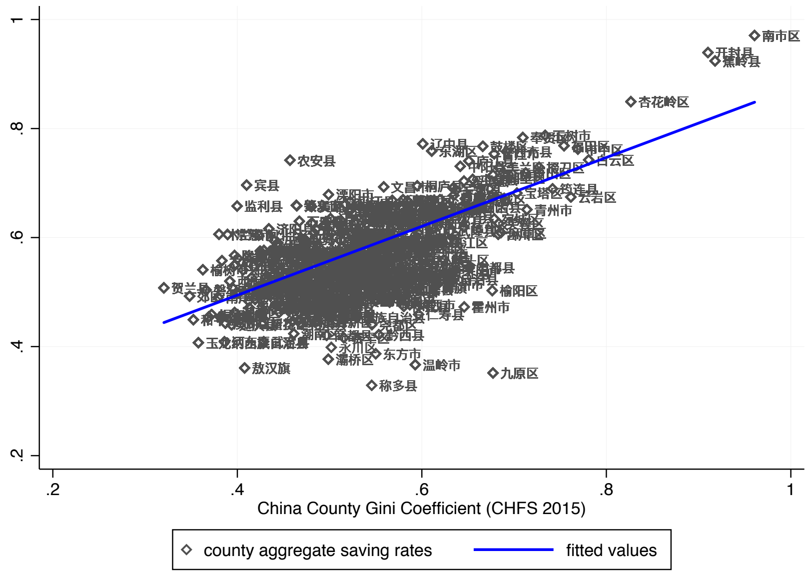
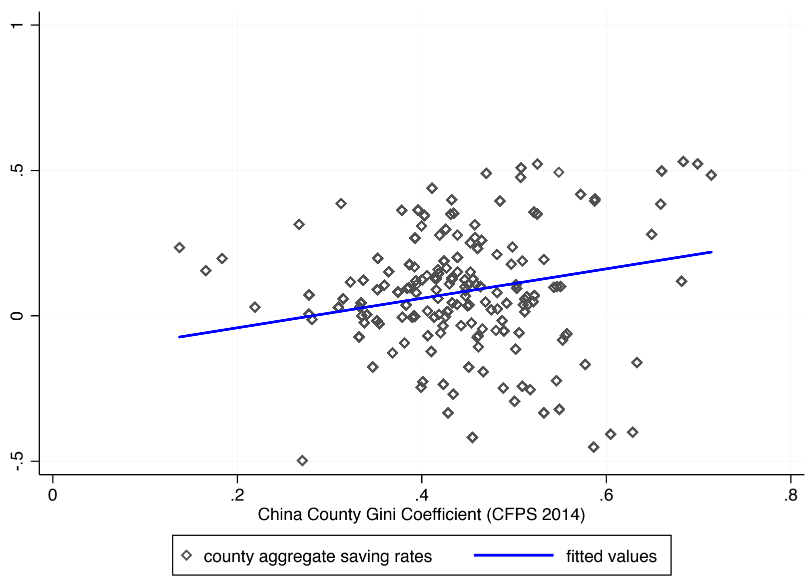


Figure A.4: County-level aggregate saving rate and Gini coefficient

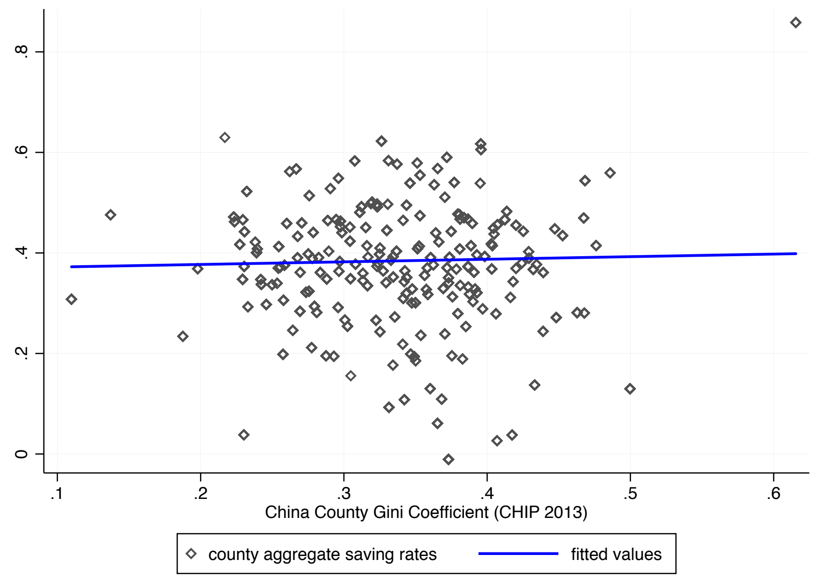


(1) CHFS 2015



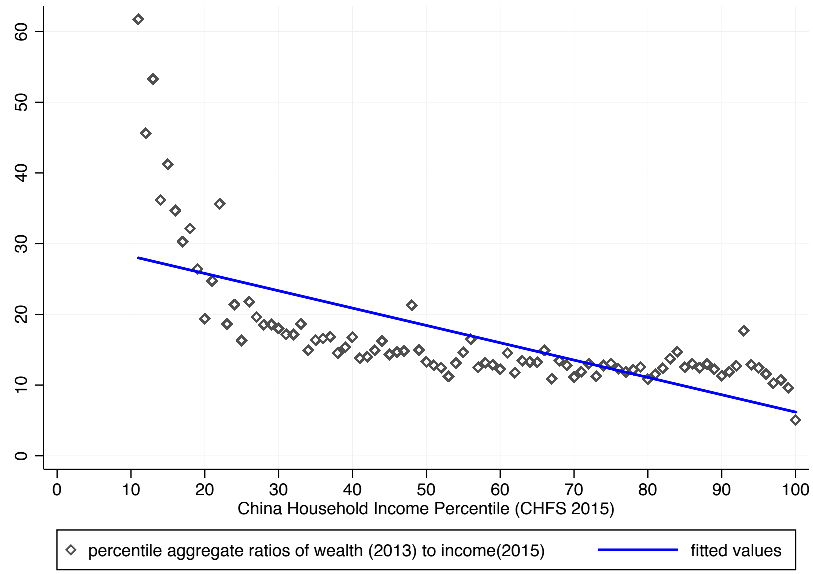
(2) CFPS 2014

Figure A.4: County-level aggregate saving rate and Gini coefficient continued

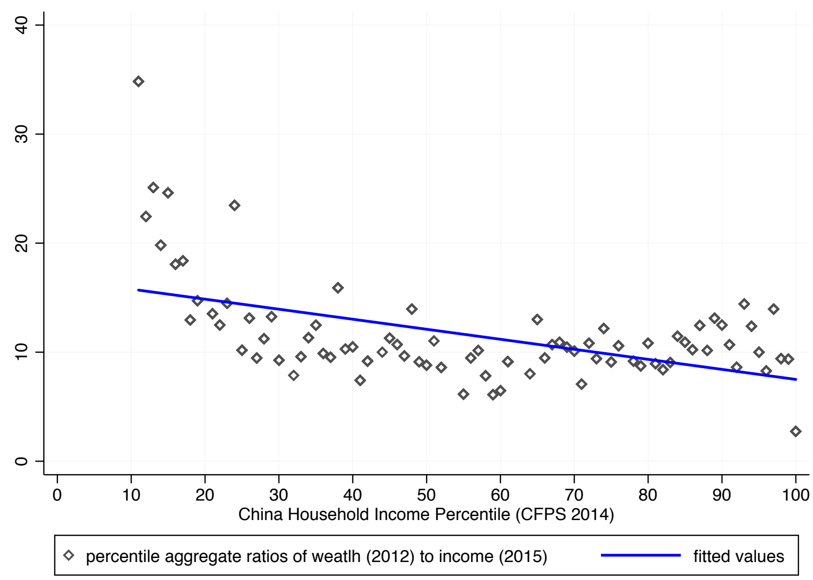


(3) CHIP 2013

Figure A.5: The ratio of previous wealth to current income by income percentile



(1) CHFS



(2) CFPS

A.2 Tables

Table A.1: The uneven distribution of China's household saving rate

	CHFS 2015		CFPS 2014		CHIP 2013		NBS
	saving rate	shares	saving rate	shares	saving rate	shares	saving rate
top 1%	0.866	69.1	0.581	44.0	0.536	12.2	
top 5%	0.741	99.7	0.515	76.7	0.426	29.3	
top 10%	0.672	116.0	0.471	96.6	0.403	44.4	
top 25%	0.569	138.2	0.412	133.6	0.373	73.5	
bottom 50%	-1.327	-45.8	-0.634	-52.8	0.017	1.35	
% savers	55.9		45.3		74.6		
saving rate (2015)	0.291						0.285
saving rate (2014)			0.189				0.281
saving rate (2013)					0.273		0.278

Table A.2: Liquidity constraints and saving rate by income group

(a) CHFS 2015 Urban

	measure I			measure II		
	FA < 2 mon. PI		FA ≥ 2 mon. PI	no CC		at least one CC
	% constrained	s.r	s.r.	% constrained	s.r	s.r
top 20%	16.93	0.769	0.389	59.51	0.545	0.435
middle income	31.52	0.125	0.003	81.65	0.096	-0.179
bottom 20%	37.78	-0.794	-1.587	92.27	-1.142	-2.677

(b) CFPS 2014 Urban

	measure I		
	FA < 2 mon. PI		FA ≥ 2 mon. PI
	% constrained	s.r	s.r.
top 20%	43.01	0.338	0.242
middle income	43.04	-0.015	-0.071
bottom 20%	58.53	-0.781	-0.977

(c) CHIP 2013 Urban

	measure I		
	FA < 2 mon. PI		FA ≥ 2 mon. PI
	% constrained	s.r	s.r.
top 20%	15.81	0.422	0.403
middle income	14.40	0.388	0.306
bottom 20%	21.31	0.310	0.2595

Table A.3: Definition of variables and summary statistics

(a) Definition of variables

Variable	Description
household consumption	sum of family members' expenditure on food, clothing, housing, appliance and commodities, communication and transportation, culture recreation and entertainment, medical care and others
household income	sum of family members' wage income, business income, agricultural income, investment income and transfer income
hh_income_i	dummy variable, equals one if the household income is in the ith quintile and zero otherwise
hh_size	total number of members in the family
YDratio	number of age 0-14 in the household divided by hh_size
ODratio	number of age above 65 in the household divided by hh_size
employed	dummy variable, takes one if currently employed
employed_typ_j	dummy variable, equals one if household head works in type j organization, $j = 1$ (SOE, collective, or government), 2 (private or foreign company), or 3 (others)
hukou	dummy variable, takes one for urban and 0 for rural
hh_health	dummy variable, equals one if the household has a poor health member and zero otherwise
health_insurance	dummy variable, takes one if the household has health insurance and zero otherwise
pension	dummy variable, equals one if the household has pension and zero otherwise.
house_owner	dummy variable, takes one if the household own house and zero otherwise.
boy_number	number of boys in the household
girl_number	number of girls in the household
childage_04/59/1014/1519	dummy variables, takes one for child's age between 0 and 4 / between 5 and 9/ between 10 and 14/between 15 and 19)
age	age of household head
age2	age square
gender	dummy variable, takes one for male and zero for female
married	dummy variable, equals one for married household head and zero for unmarried household head
ccp_member	dummy variable, takes one for ccp member and zero otherwise
yos	years of schooling
hh_credit	dummy variable, equals one for constrained household and zero for unconstrained household

Table A.3: Definition of variables and summary statistics continued

(b) Summary of statistics: CHFS 2015

Variable	Obs	Mean	Std.Dev.	Min	Max
hh size	25,635	3.177	1.449	1	20
YDratio	25,634	0.117	0.162	0	1
ODratio	25,634	0.170	0.318	0	1
employed	25,563	0.591	0.492	0	1
employ type	10,248	1.775	0.737	1	3
industry	9,342	11.28	6.968	1	24
hukou	24,377	0.607	0.488	0	1
health	25,584	0.186	0.389	0	1
hh health	25,628	0.314	0.464	0	1
health insurance	25,635	0.914	0.280	0	1
pension	25,169	0.792	0.406	0	1
house owner	22,802	0.990	0.0997	0	1
boy number	25,635	0.340	0.546	0	4
girl number	25,635	0.260	0.517	0	5
childage_04	25,635	0.134	0.377	0	7
childage_59	25,635	0.155	0.397	0	5
childage_1014	25,635	0.132	0.364	0	6
childage_1519	25,635	0.143	0.382	0	5
age	25,628	52.13	14.96	3	101
age2	25,628	2941	1607	9	10201
gender	25,635	0.699	0.459	0	1
married	23,304	0.834	0.372	0	1
ccp member	24,079	0.113	0.316	0	1
yos	25,598	10.28	4.098	0	22
hh credit	25,635	0.721	0.448	0	1

Table A.3: Definition of variables and summary statistics continued

(c) Summary of statistics: CFPS 2014

Variable	Obs	Mean	Std.Dev.	Min	Max
hh size	6,603	3.005	1.578	1	14
YDratio	6,603	0.136	0.183	0	1
ODratio	6,603	0.150	0.306	0	1
employed	6,255	0.600	0.490	0	1
employ type	2,641	1.777	0.647	1	3
industry	3,117	8.100	5.188	1	19
hukou	6,387	0.514	0.500	0	1
health	6,597	0.170	0.376	0	1
hh health	6,598	0.273	0.446	0	1
health insurance	6,603	0.876	0.330	0	1
pension	6,603	0.406	0.491	0	1
house owner	6,599	0.821	0.383	0	1
boy number	6,603	0.359	0.573	0	4
girl number	6,603	0.303	0.566	0	5
childage_04	6,603	0.167	0.431	0	4
childage_59	6,603	0.166	0.430	0	4
childage_1014	6,603	0.143	0.379	0	3
childage_1519	6,603	0.154	0.396	0	3
age	6,603	54.37	16.30	0	102
age2	6,603	3221	1792	0	10404
gender	6,603	0.669	0.471	0	1
ethnicity	597	0.0704	0.256	0	1
married	6,600	0.767	0.423	0	1
ccp member	6,603	0.125	0.331	0	1
yos	6,600	7.987	4.870	0	19
schooling	6,600	1.441	0.708	1	3
hh credit	5,986	0.545	0.498	0	1

Table A.3: Definition of variables and summary statistics continued

(d) Summary of statistics: CHIP 2013

Variable	Obs	Mean	Std.Dev.	Min	Max
hh size	6,674	2.980	1.107	1	8
YDratio	6,674	0.121	0.162	0	0.667
ODratio	6,674	0.121	0.283	0	1
employed	6,674	0.677	0.468	0	1
employ type	4,515	1.604	0.652	1	3
industry	4,513	9.779	5.993	1	20
hukou	6,672	0.844	0.363	0	1
health	6,667	0.0601	0.238	0	1
hh health	6,670	0.115	0.319	0	1
health insurance	6,640	1.733	6.005	0	156
pension	6,597	1.232	3.533	0	163
house owner	6,322	0.966	0.180	0	1
boy number	6,674	0.309	0.496	0	3
girl number	6,674	0.250	0.471	0	3
childage_04	6,674	0.109	0.324	0	2
childage_59	6,674	0.131	0.350	0	2
childage_1014	6,674	0.138	0.356	0	2
childage_1519	6,674	0.150	0.379	0	3
age	6,674	50.22	13.18	17	97
age2	6,674	2696	1400	289	9409
gender	6,674	0.728	0.445	0	1
ethnicity	6,673	0.0451	0.208	0	1
married	6,672	1.112	0.315	1	2
ccp member	6,634	0.276	0.447	0	1
yos	6,672	11.34	3.555	0	21
hh credit	6,331	0.840	0.366	0	1

Table A.4: The rich do save more

(a) Saving rate and current income

	CHFS 2015 Urban		CFPS 2014 Urban		CHIP 2013 Urban	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
hh_income_2	0.303***	0.305***	0.257***	0.247***	0.0731***	0.0868***
	(0.0157)	(0.0221)	(0.0203)	(0.0394)	(0.0139)	(0.0160)
hh_income_3	0.462***	0.453***	0.349***	0.292***	0.135***	0.166***
	(0.0149)	(0.0213)	(0.0215)	(0.0396)	(0.0143)	(0.0147)
hh_income_4	0.582***	0.553***	0.464***	0.385***	0.178***	0.186***
	(0.0154)	(0.0202)	(0.0224)	(0.0392)	(0.0142)	(0.0146)
hh_income_5	0.783***	0.750***	0.628***	0.544***	0.241***	0.262***
	(0.0159)	(0.0204)	(0.0238)	(0.0419)	(0.0131)	(0.0156)
hh_size	-0.0219***	-0.0214***	-0.0267***	-0.0498***	-0.000924	-0.00535
	(0.00459)	(0.00705)	(0.00844)	(0.0148)	(0.00604)	(0.00819)
YDratio	-0.0730	0.0245	-0.155*	-0.240*	-0.105**	-0.0499
	(0.0486)	(0.0609)	(0.0829)	(0.132)	(0.0462)	(0.0580)
ODratio	0.0656*	0.0989*	0.0653**	-0.115	0.0674***	0.0105
	(0.0395)	(0.0571)	(0.0264)	(0.115)	(0.0202)	(0.0484)
employed	0.0837***	0.0837***	0.00187	0.0397	0.0463***	0.0923
	(0.0108)	(0.0108)	(0.0154)	(0.0422)	(0.0138)	(0.107)
employ_typ_2		0.00141		0.0682**		-0.00404
		(0.0121)		(0.0321)		(0.0131)
employ_typ_3		0.00914		0.0126		0.00648
		(0.0136)		(0.0496)		(0.0236)
hukou	-0.0234**	-0.00854	-0.113***	-0.103***	0.000936	-0.000357
	(0.00923)	(0.0127)	(0.0141)	(0.0308)	(0.00986)	(0.0123)
hh_health	-0.0152*	-0.0214	-0.0220	-0.103***	-0.0404***	-0.0349**
	(0.00862)	(0.0146)	(0.0162)	(0.0341)	(0.0150)	(0.0173)
health_insurance	-0.0201	-0.0393*	0.0357	-0.0290	-0.00103	-0.00130**
	(0.0144)	(0.0239)	(0.0263)	(0.0441)	(0.000721)	(0.000663)
pension	-0.00293	0.0162	0.00969	0.0114	0.000624	-0.000582
	(0.0120)	(0.0176)	(0.0177)	(0.0296)	(0.00165)	(0.00211)
house_owner	-0.0458*	-0.0582	0.0672***	0.0647**	0.00454	-0.0303
	(0.0265)	(0.0494)	(0.0170)	(0.0275)	(0.0239)	(0.0291)
boy_number	-0.0756**	-0.0222	-0.0440	-0.000347	-0.0401	-0.0225
	(0.0319)	(0.0295)	(0.0441)	(0.0475)	(0.0253)	(0.0255)
girl_number	-0.0822**	-0.0288	-0.0582	0.0145	-0.0489*	-0.0337
	(0.0323)	(0.0335)	(0.0477)	(0.0540)	(0.0266)	(0.0271)
childage_04	0.0917**	0.0327	0.0720	0.122*	0.0332	0.0162
	(0.0358)	(0.0318)	(0.0510)	(0.0702)	(0.0281)	(0.0325)
childage_59	0.0621*	-0.00946	0.0645	0.0712	0.0491	0.0275
	(0.0345)	(0.0323)	(0.0498)	(0.0576)	(0.0305)	(0.0320)
childage_1014	0.0465	-0.0113	0.0827	0.105	0.0463*	0.0198
	(0.0338)	(0.0304)	(0.0515)	(0.0678)	(0.0278)	(0.0301)
childage_1519	0.0185	-0.0275	-0.00349	-0.00794	0.0238	0.0216
	(0.0325)	(0.0294)	(0.0513)	(0.0623)	(0.0273)	(0.0268)
age	0.00579*	-0.00313	0.00431	-0.0133*	0.000673	-0.00655
	(0.00316)	(0.00442)	(0.00303)	(0.00755)	(0.00236)	(0.00431)
age2	-2.50e-05	6.81e-05	-4.22e-05	0.000195**	-5.86e-06	8.62e-05*
	(3.36e-05)	(4.98e-05)	(2.83e-05)	(8.49e-05)	(2.47e-05)	(4.78e-05)
gender	0.0327***	0.0322***	0.0225	0.0118	0.0336***	0.0226*
	(0.00883)	(0.0122)	(0.0147)	(0.0284)	(0.00953)	(0.0119)
married	-0.0335**	-0.00862	-0.0729***	-0.0355	-0.000690	0.0266
	(0.0139)	(0.0216)	(0.0183)	(0.0342)	(0.0144)	(0.0240)
ccp_member	-0.0192*	-0.0233	-0.0410**	-0.0497	-0.0130	-0.0119
	(0.0106)	(0.0148)	(0.0174)	(0.0349)	(0.0110)	(0.0135)
yos	-0.00794***	-0.0102***	-0.00898***	-0.00130	-0.00589***	-0.00753***
	(0.00161)	(0.00213)	(0.00158)	(0.00352)	(0.00134)	(0.00195)
hh_credit	-0.104***	-0.0903***	-0.0181	0.0117	0.0976***	0.0789***
	(0.00872)	(0.0118)	(0.0130)	(0.0273)	(0.0145)	(0.0176)
Province FE	YES	YES	YES	YES	YES	YES
Constant	-0.0512	0.281***	-0.0442	0.419**	0.167**	0.348**
	(0.0742)	(0.104)	(0.0853)	(0.202)	(0.0799)	(0.172)
Observations	11,236	5,683	4,229	1,766	5,894	4,019

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.4: The rich do save more continued

(b) Saving rate and permanent income

	CHFS 2015 Urban		CFPS 2014 Urban		CHIP 2013 Urban	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	(sub-sample reg.)	(3 years avg. inc.)	(sub-sample reg.)	(3 years avg. inc.)	(sub-sample reg.)	(3 years avg. inc.)
hh_income_2	0.347***	0.0509**	0.255***	0.0313	0.0959***	0.0832***
	(0.0307)	(0.0207)	(0.0491)	(0.0577)	(0.0182)	(0.0117)
hh_income_3	0.512***	0.120***	0.308***	0.136**	0.169***	0.136***
	(0.0317)	(0.0255)	(0.0520)	(0.0547)	(0.0196)	(0.0130)
hh_income_4	0.617***	0.156***	0.472***	0.143*	0.175***	0.166***
	(0.0300)	(0.0223)	(0.0521)	(0.0784)	(0.0174)	(0.0127)
hh_income_5	0.819***	0.190***	0.616***	0.173***	0.257***	0.234***
	(0.0319)	(0.0265)	(0.0620)	(0.0606)	(0.0194)	(0.0153)
hh_size	-0.00777	0.0283***	0.0152	-0.00168	-0.00144	0.00240
	(0.00949)	(0.00933)	(0.0321)	(0.0194)	(0.0123)	(0.00499)
YDratio	0.0391	-0.0479	-0.0291	-0.217	-0.0594	-0.0826*
	(0.0681)	(0.100)	(0.172)	(0.181)	(0.0693)	(0.0476)
ODratio	0.121	0.0466		-0.0533	-0.0343	0.0392**
	(0.0923)	(0.0633)	(0.0947)	(0.0770)	(0.0176)	
employed	0.0648*	0.113***	0.0347	0.0126	0.0208	0.0419***
	(0.0363)	(0.0235)	(0.0751)	(0.0467)	(0.0353)	(0.0117)
hukou	-0.00258	0.00891	-0.0655*	-0.0630*	0.000555	-0.00260
	(0.0172)	(0.0220)	(0.0391)	(0.0361)	(0.0173)	(0.0111)
hh_health	-0.0379**	-0.0556***	-0.0484	-0.0415	-0.0459**	-0.0424***
	(0.0182)	(0.0210)	(0.0651)	(0.0381)	(0.0219)	(0.00878)
health_insurance	0.0102	0.000288	0.00430	0.0293	-0.00100	-0.000165
	(0.0255)	(0.0350)	(0.0464)	(0.0678)	(0.00131)	(0.000617)
pension	0.0234	0.0360	0.0917***	0.0633	0.000445	-0.000399
	(0.0186)	(0.0253)	(0.0353)	(0.0443)	(0.00249)	(0.000723)
house_owner	-0.0938	-0.150**	0.0433	0.0812	-0.0296	-0.00581
	(0.0839)	(0.0662)	(0.0331)	(0.0536)	(0.0376)	(0.0252)
boy_number	-0.00880	-0.100*	-0.0447	-0.0631	0.00134	-0.0451**
	(0.0425)	(0.0514)	(0.0742)	(0.0793)	(0.0328)	(0.0178)
girl_number	-0.0143	-0.126**	-0.0624	-0.0945	-0.0113	-0.0485**
	(0.0448)	(0.0541)	(0.0834)	(0.0864)	(0.0362)	(0.0200)
childage_04	0.00847	0.0697	0.0211	-0.000895	0.00919	0.0165
	(0.0463)	(0.0463)	(0.0962)	(0.0834)	(0.0353)	(0.0238)
childage_59	-0.0197	0.0720	0.0607	0.153*	0.00537	0.0494**
	(0.0453)	(0.0507)	(0.0847)	(0.0891)	(0.0356)	(0.0235)
childage_1014	-0.0269	0.0788	0.0540	0.109	0.00506	0.0525**
	(0.0434)	(0.0521)	(0.101)	(0.0948)	(0.0361)	(0.0238)
childage_1519	-0.0236	0.0249	0.0105	0.0698	-0.000359	0.0293
	(0.0426)	(0.0502)	(0.0838)	(0.0907)	(0.0307)	(0.0212)
age		-0.00787		0.0141		-0.00323
		(0.00606)		(0.00875)		(0.00222)
age2		9.53e-05		-8.97e-05		3.56e-05
		(6.53e-05)		(8.00e-05)		(2.23e-05)
gender	0.0228	-0.00320	0.0344	0.0498	0.0406**	0.0233**
	(0.0140)	(0.0180)	(0.0429)	(0.0425)	(0.0160)	(0.0103)
married	-0.0568*	0.0385	-0.129**	-0.0340	0.0125	-0.00566
	(0.0303)	(0.0238)	(0.0560)	(0.0524)	(0.0382)	(0.0135)
ccp_member	-0.0360	-0.0207	-0.0282	-0.0528	-0.0199	-0.0130
	(0.0223)	(0.0332)	(0.0428)	(0.0498)	(0.0156)	(0.00855)
yos	-0.00718***	0.00289	-0.00751	-0.00507	-0.00587**	-0.00576***
	(0.00242)	(0.00270)	(0.00498)	(0.00420)	(0.00257)	(0.00134)
hh_credit	-0.0975***	-0.0853***	-0.0148	0.0115	0.0970***	0.0644***
	(0.0178)	(0.0172)	(0.0337)	(0.0356)	(0.0189)	(0.0125)
Province FE	YES	YES	YES	YES	YES	YES
Constant	0.0554	0.279*	-0.133	-0.326	0.207**	0.259***
	(0.105)	(0.159)	(0.118)	(0.286)	(0.0820)	(0.0727)
Observations	3,901	6,849	965	1,030	2,149	5,879

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.4: The rich do save more continued

(c) Robust check: nonentrepreneurs and older households

VARIABLES	CHFS 2015 Urban (1) (excld. entrep.)	CHFS 2015 Urban (2) (age ≥ 60)	CFPS 2014 Urban (3) (excld. entrep.)	CFPS 2014 Urban (4) (age ≥ 60)	CHIP 2013 Urban (5) (excld. entrep.)	CHIP 2013 Urban (6) (age ≥ 60)
hh_income_2	0.436***	0.695***	0.226***	0.841***	0.0909***	0.0769***
	(0.0636)	(0.0436)	(0.0235)	(0.112)	(0.0125)	(0.0253)
hh_income_3	0.448***	0.990***	0.291***	1.164***	0.148***	0.122***
	(0.0810)	(0.0430)	(0.0245)	(0.114)	(0.0119)	(0.0304)
hh_income_4	0.864***	1.194***	0.426***	1.271***	0.184***	0.184***
	(0.0779)	(0.0505)	(0.0239)	(0.128)	(0.0133)	(0.0287)
hh_income_5	0.910***	1.445***	0.599***	1.412***	0.244***	0.274***
	(0.0902)	(0.0527)	(0.0240)	(0.140)	(0.0154)	(0.0351)
hh_size	-0.0649**	-0.0345**	-0.0336***	-0.0531	0.00122	-0.00758
	(0.0280)	(0.0147)	(0.0105)	(0.0377)	(0.00516)	(0.0160)
YDratio	-0.224	-0.611***	-0.180**	0.504	-0.0793	-0.336
	(0.372)	(0.231)	(0.0846)	(0.389)	(0.0499)	(0.227)
ODratio	-0.486	0.107***	0.0292	0.323**	0.0448***	0.0122
	(0.329)	(0.0286)	(0.0462)	(0.144)	(0.0170)	(0.0394)
employed	0.117	0.181***	0.00277	0.193**	0.0355***	0.0892***
	(0.0746)	(0.0378)	(0.0214)	(0.0840)	(0.0120)	(0.0292)
hukou	0.0476	-0.0303	-0.112***	-0.141	-0.00145	0.0110
	(0.0544)	(0.0307)	(0.0193)	(0.107)	(0.0119)	(0.0278)
hh_health	0.0558	-0.104***	-0.0109	-0.0174	-0.0373***	-0.0546***
	(0.0671)	(0.0212)	(0.0179)	(0.0485)	(0.00864)	(0.0207)
health_insurance	-0.0409	0.00727	0.0465	-0.148	-0.000311	0.00239
	(0.0876)	(0.0721)	(0.0293)	(0.0895)	(0.000678)	(0.00193)
pension	0.127*	0.00395	-0.00722	-0.0806	-0.000471	0.00630
	(0.0724)	(0.0443)	(0.0180)	(0.165)	(0.000769)	(0.00440)
house_owner	-0.786***	0.0836	0.0411*	0.0578	0.00176	0.104**
	(0.177)	(0.115)	(0.0215)	(0.0937)	(0.0244)	(0.0443)
boy_number	-0.00417	-0.0741	0.0142	-0.0546	-0.0457**	-0.0784
	(0.0957)	(0.0878)	(0.0402)	(0.155)	(0.0181)	(0.0657)
girl_number	-0.0214	-0.0198	0.0116	-0.0772	-0.0476**	-0.0488
	(0.113)	(0.0941)	(0.0435)	(0.152)	(0.0202)	(0.0733)
childage_04	0.0703	0.0946	0.0249	-0.122	0.0122	0.0717
	(0.160)	(0.0994)	(0.0483)	(0.152)	(0.0251)	(0.0916)
childage_59	0.0681	0.123	0.0135	-0.0137	0.0476*	0.124
	(0.145)	(0.111)	(0.0484)	(0.147)	(0.0245)	(0.0903)
childage_1014	0.130	0.107	0.0312	0.0665	0.0546**	0.143
	(0.147)	(0.106)	(0.0503)	(0.139)	(0.0256)	(0.0891)
childage_1519	-0.0256	-0.0515	-0.0362	-0.000626	0.0291	-0.0161
	(0.103)	(0.0952)	(0.0475)	(0.158)	(0.0221)	(0.0778)
age	0.0282	0.00475	-0.0190	-0.00341	0.0480	
	(0.0268)	(0.00380)	(0.0816)	(0.00215)	(0.0294)	
age2	-0.000295	-3.58e-05	9.37e-05	3.47e-05	-0.000313	
	(0.000277)	(3.60e-05)	(0.000540)	(2.15e-05)	(0.000202)	
gender	-0.00232	0.0712***	0.0294	0.162**	0.0235**	0.0165
	(0.0555)	(0.0240)	(0.0186)	(0.0738)	(0.0106)	(0.0258)
married	-0.103	-0.100***	-0.0685***	-0.108	-0.00565	-0.0155
	(0.0900)	(0.0348)	(0.0231)	(0.0816)	(0.0133)	(0.0285)
ccp_member	-0.0305	0.0276	-0.0602***	-0.0385	-0.0125	0.00554
	(0.106)	(0.0349)	(0.0225)	(0.0597)	(0.00873)	(0.0207)
yos	-0.0264**	-0.00904**	-0.00764***	-0.0156**	-0.00662***	-0.00705**
	(0.0104)	(0.00353)	(0.00202)	(0.00721)	(0.00140)	(0.00312)
hh_credit	0.0184	-0.0864***	-0.00521	-0.0550	0.0709***	0.0907**
Province FE	YES	YES	YES	YES	YES	YES
	(0.0483)	(0.0226)	(0.0166)	(0.0668)	(0.0121)	(0.0358)
constant	0.394	-0.747***	-0.189*	0.231	0.263***	-1.563
	(0.667)	(0.141)	(0.105)	(2.989)	(0.0723)	(1.047)
Observations	5,243	5,380	4,228	1,633	5,555	1,182

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.4: The rich do save more continued

(d) Robust check: per capital income and alternative definition of saving rate

	CHFS 2015 Urban		CFPS 2014 Urban		CHIP 2013 Urban	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	(redef. s.r.)	(re-grouped)	(redef. s.r.)	(re-grouped)	(redef. s.r.)	(re-grouped)
hh_income_2	0.326***	0.347***	0.257***	0.208***	0.128***	0.0842***
	(0.0213)	(0.0287)	(0.0289)	(0.0610)	(0.0186)	(0.0193)
hh_income_3	0.529***	0.519***	0.349***	0.309***	0.222***	0.151***
	(0.0231)	(0.0273)	(0.0332)	(0.0657)	(0.0192)	(0.0201)
hh_income_4	0.739***	0.635***	0.533***	0.451***	0.289***	0.190***
	(0.0233)	(0.0273)	(0.0310)	(0.0591)	(0.0206)	(0.0203)
hh_income_5	1.208***	0.829***	0.858***	0.625***	0.431***	0.251***
	(0.0328)	(0.0290)	(0.0387)	(0.0600)	(0.0286)	(0.0188)
hh_size	-0.0266**	0.0661***	-0.0476***	0.0715**	0.00703	0.0441***
	(0.0105)	(0.0113)	(0.0154)	(0.0344)	(0.00837)	(0.0148)
YDratio	-0.0258	0.0511	-0.315***	-0.121	-0.0940	-0.0811
	(0.0938)	(0.0795)	(0.107)	(0.183)	(0.0779)	(0.0781)
ODratio	0.0213	0.162**	0.0327	-0.0950	0.0853***	-0.0993
	(0.0766)	(0.0750)	(0.0613)	(0.0678)	(0.0308)	(0.0947)
employed	0.0799***	0.116***	0.0116	0.116***	0.0597***	0.0153
	(0.0194)	(0.0296)	(0.0302)	(0.0296)	(0.0182)	(0.0422)
hukou	-0.0442**	-0.000267	-0.185***	-0.0320	-0.0134	-0.00190
	(0.0188)	(0.0187)	(0.0288)	(0.0414)	(0.0223)	(0.0144)
hh_health	-0.0281	-0.0481**	-0.0171	-0.0623	-0.0674***	-0.0299
	(0.0175)	(0.0216)	(0.0271)	(0.0619)	(0.0140)	(0.0191)
health_insurance	0.000201	-0.00388	0.0699*	-0.0478	0.000656	-0.00103
	(0.0318)	(0.0290)	(0.0378)	(0.0540)	(0.00151)	(0.00140)
pension	-0.00141	0.000259	-0.0111	0.120***	-0.00162	0.000593
	(0.0210)	(0.0219)	(0.0233)	(0.0374)	(0.00134)	(0.00228)
house_owner	-0.122**	-0.0510	0.0546*	0.102**	-0.0118	-0.0215
	(0.0612)	(0.0849)	(0.0310)	(0.0414)	(0.0436)	(0.0393)
boy_number	-0.115**	-0.0191	-0.0165	0.0188	-0.0738**	-0.0145
	(0.0478)	(0.0407)	(0.0515)	(0.0846)	(0.0294)	(0.0373)
girl_number	-0.142***	-0.0156	-0.0233	0.0206	-0.0841**	-0.0230
	(0.0514)	(0.0428)	(0.0586)	(0.0866)	(0.0335)	(0.0387)
childage_04	0.119**	0.0293	0.0716	-0.0368	0.0130	0.00650
	(0.0520)	(0.0464)	(0.0641)	(0.106)	(0.0392)	(0.0451)
childage_59	0.0713	0.0125	0.0501	0.0155	0.0612	0.0104
	(0.0575)	(0.0454)	(0.0629)	(0.103)	(0.0389)	(0.0419)
childage_1014	0.0762	-0.0146	0.0799	0.00798	0.0703*	0.0160
	(0.0528)	(0.0425)	(0.0667)	(0.108)	(0.0392)	(0.0426)
childage_1519	0.0241	-0.0203	-0.000193	-0.00355	0.0366	0.00482
	(0.0520)	(0.0432)	(0.0613)	(0.0913)	(0.0340)	(0.0334)
age	0.00519	-0.0235	0.00925*	0.00111	-0.00435	0.0216
	(0.00782)	(0.0278)	(0.00533)	(0.000894)	(0.00379)	(0.0280)
age2	-1.35e-05	0.000396	-7.66e-05	0.0173	4.27e-05	-0.000300
	(8.23e-05)	(0.000367)	(5.21e-05)	(0.0409)	(3.75e-05)	(0.000370)
gender	0.0341*	0.0154	0.0471*	-0.0109	0.0354**	0.0410***
	(0.0189)	(0.0137)	(0.0249)	(0.0631)	(0.0159)	(0.0152)
married	-0.0422*	-0.000399	-0.109***	-0.0363	0.00144	-0.0187
	(0.0237)	(0.0389)	(0.0320)	(0.0499)	(0.0201)	(0.0335)
ccp_member	0.00961	-0.0272	-0.0828***	-0.0157	-0.0186	-0.0177
	(0.0293)	(0.0193)	(0.0280)	(0.0670)	(0.0145)	(0.0151)
yos	-0.0136***	-0.00508**	-0.0119***	-0.0133***	-0.0112***	-0.00564**
	(0.00275)	(0.00249)	(0.00291)	(0.00511)	(0.00234)	(0.00230)
hh_credit	-0.202***	-0.101***	-0.0475**	-0.0131	0.0731***	0.120***
	(0.0187)	(0.0180)	(0.0233)	(0.0348)	(0.0205)	(0.0230)
Province FE	YES	YES	YES	YES	YES	YES
Constant	0.0845	-0.0323	-0.148	1.683	0.399***	-0.293
	(0.179)	(0.532)	(0.138)	(1.247)	(0.123)	(0.523)
Observations	11,236	3,901	4,228	965	5,894	2,149

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.4: The rich do save more continued

(e) Check validity of the theoretical model

VARIABLES	CHFS 2015 Urban (1) hh_savingrate	(2) hh_(prev. w/curr. inc.)	(3) hh_savingrate	CFPS 2014 Urban (4) hh_savingrate	(5) hh_(prev. w/curr. inc.)	(6) hh_savingrate
hh_(prev. w/curr. inc.)			-0.00226***			-0.00288***
			(0.000436)			(0.000769)
hh_income_2	0.286***	-6.333***	0.290***	0.226***	-4.402***	0.224***
	(0.0173)	(1.200)	(0.0220)	(0.0235)	(1.123)	(0.0276)
hh_income_3	0.442***	-10.23***	0.434***	0.291***	-5.906***	0.277***
	(0.0176)	(1.029)	(0.0240)	(0.0245)	(1.171)	(0.0275)
hh_income_4	0.556***	-12.15***	0.534***	0.426***	-6.838***	0.418***
	(0.0181)	(1.126)	(0.0218)	(0.0239)	(1.099)	(0.0291)
hh_income_5	0.756***	-15.00***	0.719***	0.599***	-8.061***	0.580***
	(0.0199)	(1.355)	(0.0272)	(0.0240)	(1.174)	(0.0285)
hh_size	-0.0235***	-0.205	-0.0201**	-0.0336***	-0.488*	-0.0338***
	(0.00734)	(0.327)	(0.00833)	(0.0105)	(0.282)	(0.0112)
YDratio	0.0205	-2.921	-0.0429	-0.180**	1.766	-0.145
	(0.0748)	(2.679)	(0.0807)	(0.0846)	(2.168)	(0.101)
ODratio	0.0528	0.854	0.0409	0.0292	2.372	0.0455
	(0.0594)	(1.974)	(0.0625)	(0.0462)	(1.464)	(0.0507)
employed	0.0595***	1.290	0.0563***	0.00277	1.771**	0.00814
	(0.0147)	(1.111)	(0.0165)	(0.0214)	(0.736)	(0.0242)
hukou	-0.0181	1.192	-0.0198	-0.112***	-0.0575	-0.106***
	(0.0127)	(0.838)	(0.0194)	(0.0193)	(0.697)	(0.0232)
hh_health	-0.0168	-1.298*	-0.00522	-0.0109	-0.775	-0.0109
	(0.0144)	(0.705)	(0.0162)	(0.0179)	(0.764)	(0.0204)
health_insurance	0.00298	-1.973**	0.0112	0.0465	-1.112	0.0674*
	(0.0227)	(0.883)	(0.0284)	(0.0293)	(1.100)	(0.0366)
pension	-0.00220	1.332*	0.00602	-0.00722	-0.597	-0.0192
	(0.0144)	(0.728)	(0.0187)	(0.0180)	(0.585)	(0.0206)
house_owner	-0.0882**	6.180***	-0.179***	0.0411*	3.493***	0.0749***
	(0.0412)	(1.618)	(0.0487)	(0.0215)	(0.949)	(0.0273)
boy_number	-0.0718**	-0.00158	-0.0975**	0.0142	0.0599	-0.00257
	(0.0341)	(0.959)	(0.0452)	(0.0402)	(0.874)	(0.0476)
girl_number	-0.0923**	-0.385	-0.110**	0.0116	-0.507	-0.00326
	(0.0374)	(1.144)	(0.0466)	(0.0435)	(0.999)	(0.0512)
childage_04	0.0855**	1.940	0.122***	0.0249	1.043	0.0205
	(0.0379)	(1.255)	(0.0430)	(0.0483)	(1.008)	(0.0563)
childage_59	0.0487	1.567	0.101**	0.0135	1.882	0.0256
	(0.0427)	(1.258)	(0.0490)	(0.0484)	(1.234)	(0.0531)
childage_1014	0.0605	1.106	0.0904*	0.0312	0.527	0.0385
	(0.0389)	(1.321)	(0.0460)	(0.0503)	(1.142)	(0.0579)
childage_1519	0.0176	0.604	0.0538	-0.0362	0.770	-0.0363
	(0.0381)	(1.228)	(0.0446)	(0.0475)	(1.085)	(0.0559)
age	0.00428	-0.00525	0.00471	0.00475	0.403***	0.0121***
	(0.00483)	(0.218)	(0.00566)	(0.00380)	(0.115)	(0.00424)
age2	-1.06e-05	0.00188	-2.57e-05	-3.58e-05	-0.00260**	-0.000101***
	(5.21e-05)	(0.00244)	(5.97e-05)	(3.60e-05)	(0.00106)	(3.83e-05)
gender	0.0197	0.0995	0.0145	0.0294	-1.200*	0.0385*
	(0.0139)	(0.874)	(0.0174)	(0.0186)	(0.656)	(0.0220)
married	-0.0200	-1.114	-0.0323	-0.0685***	0.886	-0.0737***
	(0.0175)	(1.606)	(0.0245)	(0.0231)	(0.828)	(0.0270)
ccp_member	0.00140	-2.071**	-0.0103	-0.0602***	0.229	-0.0614***
	(0.0221)	(0.992)	(0.0326)	(0.0225)	(0.765)	(0.0227)
yos	-0.00793***	0.274***	-0.00717***	-0.00764***	0.283**	-0.00737***
	(0.00196)	(0.0974)	(0.00230)	(0.00202)	(0.115)	(0.00236)
hh_credit	-0.108***	2.797***	-0.0980***	-0.00521	1.653**	0.00170
	(0.0130)	(0.848)	(0.0146)	(0.0166)	(0.749)	(0.0182)
Province FE	YES	YES	YES	YES	YES	YES
Constant	-0.110	17.19***	0.0745	-0.189*	4.290	-0.386***
	(0.116)	(5.056)	(0.140)	(0.105)	(4.401)	(0.131)
Observations	6,849	6,849	6,849	3,235	3,235	3,235

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.5: The poor are more likely to face liquidity constraints

(a) CHFS 2015 Urban

VARIABLES	(1) (f.a. measure)	(2) (f.a. measure) (3 years avg. inc.)	(3) (cc measure)	(4) (cc measure) (3 years avg. inc.)
hh_income_1	0.100***	0.120***	0.270***	0.174***
	(0.0200)	(0.0239)	(0.00906)	(0.0143)
hh_income_2	0.0900***	0.0685***	0.229***	0.160***
	(0.0185)	(0.0202)	(0.00886)	(0.0137)
hh_income_3	0.0545***	0.0448**	0.188***	0.119***
	(0.0171)	(0.0215)	(0.00922)	(0.0148)
hh_income_4	0.0204	0.00889	0.130***	0.0723***
	(0.0164)	(0.0199)	(0.00969)	(0.0149)
hh_size	0.0116**	0.0102	3.34e-05	-0.0273***
	(0.00505)	(0.00652)	(0.00599)	(0.00682)
YDratio	-0.0653	-0.133*	-0.229***	-0.246***
	(0.0583)	(0.0746)	(0.0570)	(0.0677)
ODratio	-0.0210	-0.0202	0.120***	0.134**
	(0.0390)	(0.0501)	(0.0463)	(0.0550)
employed	-0.0178	-0.0172	0.0100	-0.0246
	(0.0121)	(0.0149)	(0.0150)	(0.0168)
hukou	-0.0830***	-0.0769***	-0.0883***	-0.0949***
	(0.0114)	(0.0144)	(0.0123)	(0.0142)
hh_health	0.0661***	0.0775***	0.00966	0.0341***
	(0.0109)	(0.0134)	(0.0111)	(0.0122)
health_insurance	-0.0331*	-0.0579**	-0.0275	-0.0117
	(0.0182)	(0.0240)	(0.0168)	(0.0232)
pension	-0.122***	-0.134***	-0.0702***	-0.0844***
	(0.0131)	(0.0168)	(0.0134)	(0.0154)
house_owner	-0.0219	0.0493	-0.0428	-0.0591
	(0.0489)	(0.0606)	(0.0385)	(0.0649)
age	0.00323	0.0122**	-0.0167***	0.000654
	(0.00355)	(0.00509)	(0.00386)	(0.00556)
age2	-1.60e-05	-0.000102*	0.000264***	8.48e-05
	(3.84e-05)	(5.47e-05)	(4.39e-05)	(6.19e-05)
gender	-0.0257**	-0.0136	0.0128	0.00724
	(0.0106)	(0.0137)	(0.00933)	(0.0127)
married	-0.0461***	-0.0512**	0.00962	0.00916
	(0.0159)	(0.0213)	(0.0159)	(0.0214)
ccp_member	-0.0104	0.0461	-0.0346**	-0.00545
	(0.0139)	(0.0285)	(0.0162)	(0.0263)
yos	-0.0191***	-0.0165***	-0.0273***	-0.0271***
	(0.00158)	(0.00196)	(0.00174)	(0.00214)
Province FE	YES	YES	YES	YES
Observations	11,236	6,849	11,236	6,849

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.5: The poor are more likely to face liquidity constraints continued

(b) CFPS 2014 Urban and CHIP 2013 Urban

VARIABLES	(1) (f.a. measure)	(2) (f.a. measure) (3 years avg. inc.)	(3) (f.a. measure)	(4) (f.a. measure) (3 years avg. inc.)
hh_income_1	0.232***	0.195***	0.135***	0.145***
	(0.0300)	(0.0349)	(0.0303)	(0.0272)
hh_income_2	0.204***	0.136**	0.104***	0.105***
	(0.0270)	(0.0532)	(0.0248)	(0.0246)
hh_income_3	0.0927***	0.128***	0.0412*	0.0441**
	(0.0274)	(0.0327)	(0.0232)	(0.0204)
hh_income_4	0.0553**	0.0547*	0.0658***	0.0569**
	(0.0268)	(0.0303)	(0.0219)	(0.0234)
hh_size	0.00322	0.00866	0.0178***	0.0196***
	(0.00701)	(0.00814)	(0.00639)	(0.00631)
YDratio	-2.40e-05	-0.0263	-0.00654	-0.00428
	(0.0489)	(0.0642)	(0.0409)	(0.0403)
ODratio	-0.0455	-0.0547	-0.0574**	-0.0594**
	(0.0370)	(0.0426)	(0.0277)	(0.0273)
employed	-0.0212	-0.0124	-0.0208	-0.0200
	(0.0215)	(0.0248)	(0.0149)	(0.0149)
hukou	-0.0822***	-0.0935***	0.0251	0.0231
	(0.0236)	(0.0247)	(0.0182)	(0.0184)
hh_health	0.0720***	0.0741***	0.0374**	0.0358**
	(0.0196)	(0.0230)	(0.0162)	(0.0163)
health_insurance	-0.0314	-0.0451	0.000329	0.000341
	(0.0282)	(0.0373)	(0.000554)	(0.000547)
pension	-0.00806	-0.0127	-0.00342	-0.00328
	(0.0193)	(0.0242)	(0.00235)	(0.00232)
house_owner	-0.0280	-0.0180	-0.0388	-0.0314
	(0.0203)	(0.0244)	(0.0368)	(0.0357)
age	0.00651*	0.00988**	-0.00440	-0.00436
	(0.00341)	(0.00492)	(0.00285)	(0.00280)
age2	-5.63e-05*	-7.73e-05*	3.43e-05	3.53e-05
	(3.42e-05)	(4.52e-05)	(2.71e-05)	(2.66e-05)
gender	0.00215	0.0384*	-0.00287	-0.00460
	(0.0181)	(0.0220)	(0.0132)	(0.0132)
married	-0.0412*	-0.0683**	0.0211	0.0187
	(0.0251)	(0.0308)	(0.0178)	(0.0176)
ccp_member	-0.0247	-0.0431*	0.0128	0.0132
	(0.0253)	(0.0253)	(0.0139)	(0.0139)
yos	-0.00483**	-0.00748***	-0.00162	-0.00107
	(0.00231)	(0.00269)	(0.00195)	(0.00197)
Province FE	YES	YES	YES	YES
Observations	4,387	3,016	4,907	4,898

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.6: The effect of liquidity constraints on the household saving rate

	CHFS 2015 Urban				CFPS 2014 Urban	
VARIABLES	(1) (cc measure)	(2) (cc measure)	(3) (f.a. measure)	(4) (f.a. measure)	(5) (f.a. measure)	(6) (f.a. measure)
credit × 2015	-0.278***	-0.114***	-0.263***	-0.212***	-0.264**	-0.240**
	(0.0775)	(0.0357)	(0.0673)	(0.0440)	(0.118)	(0.230)
credit	-0.0942*	-0.194***	0.0192	-0.0486*	0.0114	-0.0688***
	(0.0548)	(0.0421)	(0.0335)	(0.0252)	(0.0398)	(0.0251)
2015	-0.279***	-0.130***	0.0783	-0.0190	-0.244***	-0.159***
	(0.0368)	(0.0257)	(0.0494)	(0.0357)	(0.0437)	(0.0252)
income	2.13e-06***		1.93e-06***		9.27e-06***	
	(3.44e-07)		(2.84e-07)		(1.04e-06)	
loginc		0.756***		0.778***		0.798***
		(0.0159)		(0.0181)		(0.00912)
hh_size	0.160***	-0.0408***	0.161***	-0.0421***	0.0794***	-0.131***
	(0.0175)	(0.0121)	(0.0188)	(0.0153)	(0.0201)	(0.0102)
YDratio	-0.0321	-0.147	-0.0937	-0.197	-0.242	-0.475***
	(0.220)	(0.166)	(0.240)	(0.188)	(0.169)	(0.105)
ODratio	-0.304***	-0.00651	-0.736***	-0.224*	-0.0933	0.158***
	(0.0679)	(0.0527)	(0.159)	(0.116)	(0.0775)	(0.0459)
employed	0.185***	0.186***	0.236***	0.204***	0.103***	0.0794***
	(0.0411)	(0.0307)	(0.0441)	(0.0341)	(0.0350)	(0.0209)
hukou	0.0755**	-0.243***	0.0714*	-0.132***	-0.0817**	-0.321***
	(0.0367)	(0.0297)	(0.0405)	(0.0326)	(0.0369)	(0.0232)
hh_health	-0.180***	-0.0564**	-0.181***	-0.0539*	-0.0880***	-0.0112
	(0.0348)	(0.0277)	(0.0377)	(0.0292)	(0.0310)	(0.0184)
health_insurance	0.0278	-0.0900**	0.0601	-0.0523	-0.0136	-0.0429
	(0.0602)	(0.0422)	(0.0601)	(0.0422)	(0.0526)	(0.0300)
pension	0.248***	-0.0102	0.266***	-0.00377	-0.0313	-0.0161
	(0.0381)	(0.0287)	(0.0399)	(0.0311)	(0.0395)	(0.0242)
house_owner	0.0249	0.0960***	-0.0313	0.0146	0.156***	0.0554*
	(0.0487)	(0.0363)	(0.0527)	(0.0369)	(0.0501)	(0.0295)
boy_number	-0.164**	-0.155**	-0.199**	-0.151**	-0.0608*	-0.00537
	(0.0747)	(0.0604)	(0.0778)	(0.0639)	(0.0358)	(0.0228)
girl_number	-0.152*	-0.150**	-0.172**	-0.151**	-0.0185	-0.0118
	(0.0829)	(0.0668)	(0.0871)	(0.0712)	(0.0400)	(0.0241)
childage_04	-0.0540	0.148**	-0.0440	0.144*	-0.133**	0.135***
	(0.0895)	(0.0708)	(0.0970)	(0.0779)	(0.0545)	(0.0340)
childage_59	-0.0474	0.141**	-0.0122	0.150*	-0.116**	0.120***
	(0.0908)	(0.0702)	(0.0986)	(0.0767)	(0.0522)	(0.0328)
childage_1014	-0.0915	0.110	-0.0632	0.132	-0.0390	0.145***
	(0.0948)	(0.0749)	(0.102)	(0.0819)	(0.0589)	(0.0383)
childage_1519	-0.0888	0.0194	-0.0768	0.0236	-0.101**	-0.00102
	(0.0889)	(0.0699)	(0.0938)	(0.0742)	(0.0393)	(0.0262)
age	-0.00552	0.0179***	0.0198	0.0160	0.0183**	0.0325***
	(0.00830)	(0.00683)	(0.0134)	(0.0104)	(0.00858)	(0.00490)
age2	0.000127	-4.37e-05	-0.000165	-2.41e-05	-0.000144*	-0.000224***
	(7.78e-05)	(6.45e-05)	(0.000143)	(0.000111)	(7.92e-05)	(4.49e-05)
gender	0.00717	-0.0195	0.0641	0.0198	0.0496**	0.0690***
	(0.0380)	(0.0290)	(0.0406)	(0.0325)	(0.0208)	(0.0150)
married	-0.150***	-0.278***	-0.121**	-0.248***	-0.0555	-0.0759***
	(0.0513)	(0.0384)	(0.0574)	(0.0448)	(0.0435)	(0.0248)
ccp_member	-0.122	-0.0565	-0.141	-0.105	-0.0446	-0.127***
	(0.0911)	(0.0604)	(0.0970)	(0.0642)	(0.0508)	(0.0314)
yos	0.0170***	-0.0146***	0.0106*	-0.0253***	-0.00382	-0.0161***
	(0.00466)	(0.00362)	(0.00541)	(0.00436)	(0.00370)	(0.00227)
Province FE	YES	YES	YES	YES	YES	YES
Constant	-0.787***	-8.220***	-1.294***	-8.309***	-4.58e-06**	-8.785***
	(0.260)	(0.254)	(0.329)	(0.300)	(1.91e-06)	(0.211)
Observations	9,588	9,588	7,024	7,024	7,209	7,209
R-squared	0.231	0.558	0.243	0.576	0.237	0.579

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.7: The effect of income inequality on the aggregate household saving rate

	CHFS 2015 Urban		CFPS 2014 Urban		CHIP 2013 Urban	
VARIABLES	county_savingrate	county_savingrate	county_savingrate	county_savingrate	county_savingrate	county_savingrate
county gini	0.198*	0.176**	0.135	0.139	0.0188	0.00636
	(0.115)	(0.0710)	(0.413)	(0.412)	(0.126)	(0.125)
logcounty_pc_inc	0.322***	0.329***	0.00946*	0.00967*	0.0962***	0.107***
	(0.0178)	(0.0201)	(0.00535)	(0.00599)	(0.0223)	(0.0229)
county_YDratio		0.353		-0.0237		0.277
		(0.330)		(0.0967)		(0.177)
county_ODratio		0.583**		0.0354		-0.104
		(0.283)		(0.0744)		(0.151)
Constant	-3.093***	-3.290***	0.0301	0.0284	-0.637***	-0.761***
	(0.178)	(0.225)	(0.173)	(0.189)	(0.241)	(0.251)
Province FE	YES	YES	YES	YES	YES	YES
Observations	353	353	334	334	212	212
R-squared	0.521	0.527	0.227	0.227	0.152	0.169

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.8: The estimates of marginal propensity to consume out of transitory income

(a) CHFS Urban

VARIABLES	Quintile 1 hh_consump	Quintile 2 hh_consump	Quintile 3 hh_consump	Quintile 4 hh_consump	Quintile 5 hh_consump
hh_per_income	0.788***	0.610***	0.374*	0.541***	0.223**
	(0.112)	(0.135)	(0.191)	(0.125)	(0.0889)
hh_tran_income	0.788***	0.611***	0.364*	0.507***	0.178*
	(0.112)	(0.135)	(0.191)	(0.127)	(0.0952)
hh_netasset	0.00258	0.00267	0.00552***	0.00378*	0.00755***
	(0.00178)	(0.00189)	(0.00184)	(0.00203)	(0.00108)
hh_size	1,845***	2,256***	1,928**	-455.1	7,738**
	(520.1)	(746.1)	(964.9)	(1,603)	(2,975)
YDratio	3,356	3,752	7,838	728.0	-53,291***
	(5,460)	(5,902)	(9,017)	(9,438)	(19,647)
ODratio	255.8	1,937	-6,332**	-8,972	-6,840
	(1,664)	(3,839)	(2,968)	(6,439)	(13,406)
employed	-835.8	-3,095	-5,642	-3,028	3,586
	(1,155)	(2,406)	(3,619)	(4,439)	(6,465)
hukou	1,115	1,618	3,557	-5,127	4,924
	(1,020)	(1,945)	(2,923)	(4,383)	(6,983)
hh_health	468.2	600.7	5,046*	5,281	13,002
	(1,252)	(1,763)	(2,840)	(4,557)	(8,132)
health_insurance	818.5	-5,301*	5,876	10,938**	-37,742
	(2,548)	(2,983)	(5,334)	(4,575)	(26,362)
pension	107.5	-1,709	-354.5	8,811***	15,302
	(1,528)	(2,093)	(5,229)	(3,223)	(13,844)
house_owner	963.7	6,240	10,855**		-11,075
	(2,840)	(10,370)	(4,182)		(25,768)
age	-309.7	-405.6	-2,064**	-1,498	550.6
	(311.6)	(758.6)	(949.9)	(922.6)	(2,172)
age2	2.048	1.537	15.82*	12.43	-9.408
	(2.641)	(6.461)	(8.723)	(7.890)	(19.29)
gender	-2,579*	-2,514	-1,020	1,485	18,535
	(1,311)	(2,731)	(3,287)	(4,034)	(12,512)
married	3,402**	3,223	6,112**	6,899	4,335
	(1,501)	(2,730)	(2,465)	(7,658)	(8,798)
ccp_member	2,003	7,668	-9,152	-10,602*	1,014
	(3,108)	(4,754)	(10,935)	(6,198)	(12,878)
yos	201.1	393.1	-329.7	1,042**	19.43
	(233.7)	(388.4)	(400.1)	(443.0)	(1,212)
Province FE	YES	YES	YES	YES	YES
Constant	3,139	16,225	51,066*	48,290	6,421
	(10,747)	(23,458)	(27,895)	(39,625)	(83,059)
Observations	294	436	479	476	488
R-squared	0.650	0.220	0.222	0.228	0.238

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.8: The estimates of marginal propensity to consume out of transitory income continued

(b) CFPS Urban

VARIABLES	Quintile 1 hh_consump	Quintile 2 hh_consump	Quintile 3 hh_consump	Quintile 4 hh_consump	Quintile 5 hh_consump
hh_per_income	0.874***	0.347**	0.831***	0.486**	0.393***
	(0.102)	(0.169)	(0.198)	(0.208)	(0.126)
hh_tran_income	0.927***	0.361*	0.739***	0.477**	0.336***
	(0.0985)	(0.187)	(0.203)	(0.206)	(0.125)
hh_netasset	0.00410**	0.00453	0.00425	0.00102	0.00764**
	(0.00159)	(0.00360)	(0.00343)	(0.00196)	(0.00369)
hh_size	879.4*	1,423**	1,621	2,557**	-840.1
	(489.1)	(672.4)	(1,050)	(989.1)	(2,085)
YDratio	-1,503	-4,587	1,425	8,354	23,179
	(3,648)	(5,285)	(6,333)	(9,386)	(17,154)
ODratio	776.4	-4,393	1,852	-6,132	-6,818
	(1,785)	(3,251)	(5,194)	(6,606)	(19,803)
employed	-692.5	-1,254	3,645	5,278	8,038
	(978.3)	(2,234)	(3,030)	(3,654)	(6,518)
hukou	831.1	4,431**	3,471	7,554**	14,384**
	(1,014)	(1,708)	(2,131)	(3,533)	(6,118)
hh_health	-716.9	-363.0	2,192	-429.5	-2,001
	(749.6)	(1,979)	(2,406)	(3,483)	(5,962)
health_insurance	-94.29	624.9	38.74	-9,354	-8,738
	(1,407)	(2,759)	(2,618)	(6,569)	(8,984)
pension	1,007	-1,382	-1,900	251.4	9,983*
	(1,016)	(2,184)	(2,435)	(2,971)	(5,519)
house_owner	-2,441**	-3,162	-4,790	860.8	-3,897
	(1,155)	(2,573)	(3,417)	(3,256)	(7,581)
age	-310.8	-565.2	-1.083	-979.6	-918.4
	(325.9)	(416.9)	(551.5)	(831.7)	(1,486)
age2	1.740	4.446	-0.978	11.08	11.59
	(2.735)	(3.716)	(4.861)	(7.028)	(12.55)
gender	905.9	-2,282	-849.3	-5,015	-1,582
	(784.4)	(1,980)	(2,426)	(3,648)	(6,571)
married	-1,966*	5,344**	-40.79	9,584**	14,149**
	(1,070)	(2,071)	(2,749)	(4,458)	(5,956)
ccp_member	1,470	3,282	2,242	2,882	-461.7
	(1,513)	(2,064)	(3,024)	(3,230)	(6,547)
yos	146.4	121.6	768.0***	347.7	133.1
	(129.8)	(190.0)	(265.2)	(337.8)	(770.2)
Province FE	YES	YES	YES	YES	YES
Constant	22,369**	19,787	11,894	16,818	29,539
	(10,159)	(14,757)	(21,953)	(28,023)	(47,455)
Observations	359	489	546	572	494
R-squared	0.557	0.216	0.226	0.162	0.204

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

Table A.8: The estimates of marginal propensity to consume out of transitory income continued

(c) CHIP Urban

VARIABLES	Quintile 1 hh_consump	Quintile 2 hh_consump	Quintile 3 hh_consump	Quintile 4 hh_consump	Quintile 5 hh_consump
hh_per_income	0.613***	0.623***	0.510***	0.346***	0.233***
	(0.0287)	(0.0707)	(0.0827)	(0.0871)	(0.0806)
hh_tran_income	0.563***	0.502***	0.453***	0.308***	0.0167
	(0.0732)	(0.111)	(0.107)	(0.101)	(0.111)
hh_netasset	0.00258	-0.00342	0.00283	0.000505	0.00129
	(0.00338)	(0.00523)	(0.00306)	(0.00378)	(0.00356)
hh_size	400.5	556.1	679.0	1,246*	1,052
	(264.7)	(414.3)	(559.5)	(683.8)	(1,234)
YDratio	940.3	1,880	8,397**	-2,443	11,196
	(1,524)	(2,736)	(3,752)	(5,187)	(8,620)
ODratio	-475.2	-3,291**	-1,227	-5,937*	-16,334**
	(991.9)	(1,594)	(2,141)	(3,374)	(6,964)
employed	-1,458**	-1,731*	-2,714*	-2,834	-4,635
	(638.1)	(1,042)	(1,384)	(1,827)	(4,941)
hukou	-1,325**	80.83	1,145	-366.2	6,422
	(626.6)	(998.8)	(1,439)	(1,870)	(4,076)
hh_health	777.7*	2,542**	1,204	5,521***	1,689
	(458.1)	(997.9)	(1,389)	(1,882)	(4,341)
health_insurance	148.1	6.603	61.08	102.8	72.48
	(115.5)	(56.30)	(92.83)	(63.91)	(178.4)
pension	-32.62	-8.11	14.03	43.11	879.7
	(78.36)	(156.2)	(41.50)	(169.0)	(549.1)
house_owner	-649.5	119.0	-143.1	2,579	323.7
	(992.3)	(2,177)	(2,818)	(4,149)	(8,969)
age	-70.71	-173.2	146.3	134.9	1,110**
	(133.4)	(224.0)	(257.9)	(411.2)	(449.7)
age2	-0.0399	1.116	-1.415	-1.741	-7.981*
	(1.322)	(2.171)	(2.526)	(3.944)	(4.668)
gender	-348.6	-165.2	-1,901	-2,882*	-5,462**
	(636.8)	(861.6)	(1,275)	(1,575)	(2,609)
married	502.3	724.7	102.3	-2,231	-4,509
	(632.4)	(1,475)	(1,539)	(2,792)	(4,368)
ccp_member	-265.5	297.8	1,392	160.3	1,592
	(634.0)	(848.8)	(1,003)	(1,608)	(2,260)
yos	108.2	339.4***	480.4***	850.1***	1,617***
	(86.61)	(123.5)	(172.5)	(224.7)	(489.5)
Province FE	YES	YES	YES	YES	YES
Constant	8,524**	4,150	-634.0	12,734	1,985
	(3,964)	(8,733)	(8,572)	(15,165)	(22,473)
Observations	1,214	1,205	1,236	1,236	1,240
R-squared	0.363	0.122	0.098	0.074	0.237

Notes: 1. Robust standard errors (cluster at county level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1; 2. Standard errors in parentheses are bootstrapped 500 times for bootstrapped median regression.

APPENDIX B

INCENTIVES AND UNCERTAINTIES IN A+B PROCUREMENT CONTRACTS

B.1 Proofs

B.1.1 Proof of lemma 1

At the beginning of the construction stage, when there is a realized shock ε, the contractor chooses optimal actual working days x^A to minimize the realized total cost $(1+\varepsilon)C(x^A, \theta) + K(x^A, x^B; i, d)$, where $K(x^A, x^B, i, d) = \mathbb{I}(x^A < x^B) \cdot i \cdot (x^A - x^B) + \mathbb{I}(x^A > x^B) \cdot d \cdot (x^A - x^B)$. Intuitively, because of the daily incentive for the early completion and the daily disincentive for the delay completion, there are two critical points for the shock ε in the support, such that

$$-(1+\varepsilon^i)C_1(x^B, \theta) = i \tag{B.1}$$

$$-(1+\varepsilon^d)C_1(x^B, \theta) = d \tag{B.2}$$

for any given x^B, where $\varepsilon^i < \varepsilon^d$ since $i < d$ and $C_1(\cdot, \theta) < 0$. Notice that if the contractor completes the construction based on the bidding days, that is $x^A = x^B$, then the realized total costs, denoted as TC^0, equals $(1+\varepsilon)C(x^B, \theta)$. Depending on the realization of uncertainty ε, there are three scenarios:

Scenarios (I): The shock is "positive", namely $\varepsilon \in (-1, \varepsilon^i)$.

(i) If the contractor chooses to delay to complete the project, $x^A > x^B$, then the realized total costs, denoted as TC^+, equals $(1+\varepsilon)C(x^A, \theta) + d \cdot (x^A - x^B)$. Taking difference between

TC^0 and TC^+, we have:

$$
\begin{aligned}
TC^0 - TC^+ &= (1+\varepsilon)C(x^B, \theta) - \Big[(1+\varepsilon)C(x^A, \theta) + d \cdot (x^A - x^B)\Big] \\
&= (1+\varepsilon)\Big[C(x^B, \theta) - C(x^A, \theta)\Big] - (1+\varepsilon^d)C_1(x^B, \theta) \cdot (x^B - x^A) \\
&= (1+\varepsilon)C_1(\tilde{x}, \theta) \cdot (x^B - x^A) - (1+\varepsilon^d)C_1(x^B, \theta) \cdot (x^B - x^A) \\
&= \Big[(1+\varepsilon)C_1(\tilde{x}, \theta) - (1+\varepsilon)C_1(x^B, \theta) + (1+\varepsilon)C_1(x^B, \theta) - (1+\varepsilon^d)C_1(x^B, \theta)\Big] \cdot (x^B - x^A) \\
&= \Big\{ \underbrace{(1+\varepsilon)\Big[C_1(\tilde{x}, \theta) - C_1(x^B, \theta)\Big]}_{+} + \underbrace{(\varepsilon - \varepsilon^d)C_1(x^B, \theta)}_{+} \Big\} \cdot \underbrace{(x^B - x^A)}_{-} \\
&< 0,
\end{aligned}
$$

namely, $TC^0 < TC^+$, which implies that any choice of delay completion is worse than on-time completion. The second equality is due to plug in the Equation B.2; the third equality is obtained by the Mean-Value theorem where $x^B < \tilde{x} < x^A$; the first part in the sixth equality is positive by the assumption of the convexity of the cost function and the lower bound of the shock is -1; the second part is positive because $\varepsilon < \varepsilon^i < \varepsilon^d$ and the assumption that the cost function is decreasing in working days; the last part is negative under the condition that $x^A < x^B$.

(ii) If the contractor completes the project earlier than the bidding days, that is, $x^A < x^B$, then total realized costs, denoted as TC^-, equals $(1+\varepsilon)C(x^A, \theta) + i \cdot (x^A - x^B)$. Consider

$$
x^A = x^i \qquad \text{such that} \qquad -(1+\varepsilon)C_1(x^i, \theta) = i, \tag{B.3}
$$

combing above equation with Equation B.1, we have $x^i < x^B$ because the assumption of the convexity of the cost function and $\varepsilon < \varepsilon^i$. Let TC^i denote the total costs evaluates at x^i.

Taking difference between TC^i and TC^0, we have

$$
\begin{aligned}
TC^i - TC^0 &= \Big[(1+\varepsilon)C(x^i,\theta) + i\cdot(x^i - x^B)\Big] - (1+\varepsilon)C(x^B,\theta) \\
&= (1+\varepsilon)C(x^i,\theta) - (1+\varepsilon)C_1(x^i,\theta)\cdot(x^i - x^B) - (1+\varepsilon)C(x^B,\theta) \\
&= (1+\varepsilon)\Big[C(x^i,\theta) - C(x^B,\theta) - C_1(x^i,\theta)\cdot(x^i - x^B)\Big] \\
&= (1+\varepsilon)\Big[C_1(x',\theta)\cdot(x^i - x^B) - C_1(x^i,\theta)\cdot(x^i - x^B)\Big] \\
&= \underbrace{(1+\varepsilon)}_{+}\underbrace{\Big[C_1(x',\theta) - C_1(x^i,\theta)\Big]}_{+}\cdot\underbrace{(x^i - x^B)}_{-} \\
&< 0,
\end{aligned}
$$

namely, $TC^i < TC^0$, which implies that early completion at x^i is better than on-time completion. The second equality is obtained by plugging in the Equation B.3; the fourth equality is because the Mean-Value theorem where $x^i < x' < x^B$; the first part in the fifth equality is positive due to $\varepsilon > 1$, and the second part is positive because of the assumption of the convexity for the cost function. Next, notice that Equation B.3 is also the first-order-condition (F.O.C) for the optimal working days conditional on early completion, therefore $x^A = x^i < x^B$ is the optimal working days given the construction shock is "positive" (i.e., $\varepsilon < \varepsilon^i$).

Scenarios (II): The shock is "negative", namely $\varepsilon > \varepsilon^d$. Applying similar arguments as above, we have

$$
\begin{aligned}
TC^0 - TC^- &= (1+\varepsilon)C(x^B,\theta) - \Big[(1+\varepsilon)C(x^A,\theta) + i\cdot(x^A - x^B)\Big] \\
&= (1+\varepsilon)\Big[C(x^B,\theta) - C(x^A,\theta)\Big] - (1+\varepsilon^i)C_1(x^B,\theta)\cdot(x^B - x^A) \\
&= (1+\varepsilon)C_1(\tilde{x},\theta)\cdot(x^B - x^A) - (1+\varepsilon^i)C_1(x^B,\theta)\cdot(x^B - x^A) \\
&= \Big[(1+\varepsilon)C_1(\tilde{x},\theta) - (1+\varepsilon^i)C_1(x^B,\theta)\Big]\cdot(x^B - x^A) \\
&= \Big[(1+\varepsilon)C_1(\tilde{x},\theta) - (1+\varepsilon)C_1(x^B,\theta) + (1+\varepsilon)C_1(x^B,\theta) - (1+\varepsilon^i)C_1(x^B,\theta)\Big]\cdot(x^B - x^A) \\
&= \Big\{\underbrace{(1+\varepsilon)\Big[C_1(\tilde{x},\theta) - C_1(x^B,\theta)\Big]}_{-} + \underbrace{(\varepsilon - \varepsilon^i)C_1(x^B,\theta)}_{-}\Big\}\cdot\underbrace{(x^B - x^A)}_{+} \\
&< 0,
\end{aligned}
$$

for early completion, namely $x^A < x^B$, and

$$
\begin{aligned}
TC^d - TC^0 &= \Big[(1+\varepsilon)C(x^d,\theta) + i\cdot(x^d - x^B)\Big] - (1+\varepsilon)C(x^B,\theta) \\
&= (1+\varepsilon)C(x^d,\theta) - (1+\varepsilon)C_1(x^d,\theta)\cdot(x^d - x^B) - (1+\varepsilon)C(x^B,\theta) \\
&= (1+\varepsilon)\Big[C(x^d,\theta) - C(x^B,\theta) - C_1(x^d,\theta)\cdot(x^i - x^B)\Big] \\
&= (1+\varepsilon)\Big[C_1(x'',\theta)\cdot(x^d - x^B) - C_1(x^d,\theta)\cdot(x^d - x^B)\Big] \\
&= \underbrace{(1+\varepsilon)}_{+}\underbrace{\Big[C_1(x'',\theta) - C_1(x^d,\theta)\Big]}_{-}\cdot\underbrace{(x^d - x^B)}_{+} \\
&< 0,
\end{aligned}
$$

for delay completion at $x^A = x^d < x^B$, where x^d satisfies the F.O.C $-(1+\varepsilon)C_1(x^d,\theta) = d$. Thus, under a negative shock to construction cost function, the contractor will delay to complete the project at x^d.

Scenarios (III): The shock is “normal”, namely $\varepsilon^i \leq \varepsilon \leq \varepsilon^d$. We have

$$\begin{aligned} TC^0 - TC^- &= \Big\{ \underbrace{(1+\varepsilon)\Big[C_1(\tilde{x},\theta) - C_1(x^B,\theta)\Big]}_{-} + \underbrace{(\varepsilon - \varepsilon^i)C_1(x^B,\theta)}_{\leq 0} \Big\} \cdot \underbrace{(x^B - x^A)}_{+} \\ &< 0, \end{aligned}$$

and

$$\begin{aligned} TC^0 - TC^+ &= \Big\{ \underbrace{(1+\varepsilon)\Big[C_1(\tilde{x},\theta) - C_1(x^B,\theta)\Big]}_{+} + \underbrace{(\varepsilon - \varepsilon^d)C_1(x^B,\theta)}_{\geq 0} \Big\} \cdot \underbrace{(x^B - x^A)}_{-} \\ &< 0, \end{aligned}$$

which implies that in this case the contractor will choose actual working days not to deviate bidding days. □

Proof under the case without uncertainties

Without construction uncertainty in the execution stage, the contractor chooses optimal actual working days x^A to minimize the realized total cost $C(x^A,\theta) + K(x^A, x^B; i, d)$, where $K(x^A, x^B, i, d) = \mathbb{1}(x^A < x^B) \cdot i \cdot (x^A - x^B) + \mathbb{1}(x^A > x^B) \cdot d \cdot (x^A - x^B)$. Notice that whether or not the contractor chooses to deviate bidding days x^B solely depend on the level of x^B, whereas in the case with uncertainty, for any level of bidding days x^B, the contractor may deviate depending on the realization of shocks to cost function. Similar to the case with uncertainty, because of the daily incentive for the early completion and the daily disincentive for the delay completion, there are two critical level of bidding days such that:

$$-C_1(\tilde{x}^i, \theta) = i \tag{B.4}$$

$$-C_1(\tilde{x}^d, \theta) = d \tag{B.5}$$

where $\tilde{x}^d < \tilde{x}^i$ due to the convexity of the cost function and the assumption of $d > i$. The two values partition bidding days into three interval: (i) $x^B < \tilde{x}^d$, (ii) $\tilde{x}^d \leq x^B \leq \tilde{x}^i$, and (iii) $x^B > \tilde{x}^i$.

Case (i): If $x^B < \tilde{x}^d$, consider $x^A = \tilde{x}^d$, we have

$$\begin{aligned}
\widetilde{TC}^d - TC^0 &= \Big[C(\tilde{x}^d, \theta) + d \cdot (\tilde{x}^d - x^B)\Big] - C(x^B, \theta) \\
&= C(\tilde{x}^d, \theta) - C(x^B, \theta) - C_1(\tilde{x}^d, \theta) \cdot (\tilde{x}^d - x^B) \\
&= C_1(\tilde{x}', \theta) \cdot (\tilde{x}^d - x^B) - C_1(\tilde{x}^d, \theta) \cdot (\tilde{x}^d - x^B) \\
&= \underbrace{\Big[C_1(\tilde{x}', \theta) - C_1(\tilde{x}^d, \theta)\Big]}_{-} \cdot \underbrace{(\tilde{x}^d - x^B)}_{+} \\
&< 0,
\end{aligned}$$

where $x^B < \tilde{x}' < \tilde{x}^d$. This implies, along with the Equation B.5, that optimal actual working days will be longer than bidding days and will be set equal to $\tilde{x}^d$. The second equality is obtained by plugging in the Equation B.5, and the third equality is achieved by Mean-Value Theorem. The first part in the fourth equality is negative due to the convexity of the cost function.

Case (ii): If $\tilde{x}^d \leq x^B \leq \tilde{x}^i$, consider $x^A = x^B$, then following similar arguments, for any $\tilde{x}^A < x^B$, we have

$$\begin{aligned}
TC^0 - \widetilde{TC}^- &= C(x^B, \theta) - \Big[C(\tilde{x}^A, \theta) + i \cdot (\tilde{x}^A - x^B)\Big] \\
&= C(x^B, \theta) - C(\tilde{x}^A, \theta) - C_1(\tilde{x}^i, \theta) \cdot (x^B - \tilde{x}^A) \\
&= C_1(\tilde{x}'', \theta) \cdot (x^B - \tilde{x}^A) - C_1(\tilde{x}^i, \theta) \cdot (x^B - \tilde{x}^A) \\
&= \underbrace{\Big[C_1(\tilde{x}'', \theta) - C_1(\tilde{x}^i, \theta)\Big]}_{-} \cdot \underbrace{(x^B - \tilde{x}^A)}_{+} \\
&< 0,
\end{aligned}$$

where $\tilde{x}^A < \tilde{x}'' < x^B$; and for any $\tilde{x}^A > x^B$, we have

$$\begin{aligned}
TC^0 - \widetilde{TC}^+ &= C(x^B, \theta) - \Big[C(\tilde{x}^A, \theta) + d \cdot (\tilde{x}^A - x^B)\Big] \\
&= C(x^B, \theta) - C(\tilde{x}^A, \theta) - C_1(\tilde{x}^d, \theta) \cdot (x^B - \tilde{x}^A) \\
&= C_1(\tilde{x}''', \theta) \cdot (x^B - \tilde{x}^A) - C_1(\tilde{x}^d, \theta) \cdot (x^B - \tilde{x}^A) \\
&= \underbrace{\Big[C_1(\tilde{x}''', \theta) - C_1(\tilde{x}^d, \theta)\Big]}_{+} \cdot \underbrace{(x^B - \tilde{x}^A)}_{-} \\
&< 0,
\end{aligned}$$

where $x^B < \tilde{x}''' < \tilde{x}^A$. Thus, when bidding days $x^B \in [\tilde{x}^d, \tilde{x}^i]$, the contractor has no incentive to deviate to complete the project.

Case (iii): If $x^B > \tilde{x}^i$, consider $x^A = \tilde{x}^i$, we have

$$\begin{aligned}
\widetilde{TC}^i - TC^0 &= \Big[C(\tilde{x}^i, \theta) + i \cdot (\tilde{x}^i - x^B)\Big] - C(x^B, \theta) \\
&= C(\tilde{x}^i, \theta) - C(x^B, \theta) - C_1(\tilde{x}^i, \theta) \cdot (\tilde{x}^i - x^B) \\
&= C_1(\tilde{x}'''', \theta) \cdot (\tilde{x}^i - x^B) - C_1(\tilde{x}^i, \theta) \cdot (\tilde{x}^i - x^B) \\
&= \underbrace{\Big[C_1(\tilde{x}'''', \theta) - C_1(\tilde{x}^i, \theta)\Big]}_{+} \cdot \underbrace{(\tilde{x}^i - x^B)}_{-} \\
&< 0,
\end{aligned}$$

where $\tilde{x}^i < \tilde{x}'''' < x^B$. This implies, along with the Equation B.4, that optimal actual working days will be shorter than bidding days and will be set equal to $\tilde{x}^i$.

In summary, actual working days will depend on which interval bidding days lie in. Next, what bidding days the contractor will quote in the competition stage? Without uncertainty, optimal bidding days will be solved by the following minimization problem (by the argument in Proposition 2):

$$x^{B^*} = arg\min_{x^B} \Big\{ c_u x^B + \Big[C(x^A, \theta) + K(x^A, x^B; i, d) \Big] \Big\}. \tag{B.6}$$

Let $\widetilde{PV}$ denote $c_u \tilde{x}^B + \Big[C(x^A, \theta) + K(x^A, \tilde{x}^B; i, d) \Big]$, where $\tilde{x}^B$ satisfies $-C_1(\tilde{x}^B, \theta) = c_u$. Notice that $\tilde{x}^d < \tilde{x}^B < \tilde{x}^i$ due to the convexity of the cost function and the assumption that $i < c_u < d$, and thus $x^A = \tilde{x}^B$ and $\widetilde{PV} = c_u \tilde{x}^B + C(\tilde{x}^B, \theta)$ by the argument above. Now we can compare the value of objective function in the Equation B.6 at different bidding days. Denote PV_1 and PV_2 the value of objective function for any $x^B < \tilde{x}^d$ and for any $x^B > \tilde{x}^i$, respectively, we have

$$\begin{aligned}
\widetilde{PV} - PV_1 &= c_u \tilde{x}^B + C(\tilde{x}^B, \theta) - \Big[c_u x^B + C(\tilde{x}^d, \theta) + d \cdot (\tilde{x}^d - x^B) \Big] \\
&= c_u \cdot (\tilde{x}^B - \tilde{x}^d + \tilde{x}^d - x^B) + C(\tilde{x}^B, \theta) - C(\tilde{x}^d, \theta) - d \cdot (\tilde{x}^d - x^B) \\
&= c_u \cdot (\tilde{x}^B - \tilde{x}^d) + c_u \cdot (\tilde{x}^d - x^B) + C_1(\bar{x}, \theta) \cdot (\tilde{x}^B - \tilde{x}^d) - d \cdot (\tilde{x}^d - x^B) \\
&= \Big[c_u + C_1(\bar{x}, \theta) \Big] \cdot (\tilde{x}^B - \tilde{x}^d) + (c_u - d) \cdot (\tilde{x}^d - x^B) \\
&= \underbrace{\Big[C_1(\bar{x}, \theta) - C_1(\tilde{x}^B, \theta) \Big]}_{-} \cdot \underbrace{(\tilde{x}^B - \tilde{x}^d)}_{+} + \underbrace{(c_u - d)}_{-} \cdot \underbrace{(\tilde{x}^d - x^B)}_{+} \\
&< 0,
\end{aligned}$$

where $\tilde{x}^d < \bar{x} < \tilde{x}^B$, and

$$\begin{aligned}
\widetilde{PV} - PV_2 &= c_u \tilde{x}^B + C(\tilde{x}^B, \theta) - \Big[c_u x^B + C(\tilde{x}^i, \theta) + i \cdot (\tilde{x}^i - x^B) \Big] \\
&= \underbrace{\Big[C_1(\bar{x}', \theta) - C_1(\tilde{x}^B, \theta) \Big]}_{+} \cdot \underbrace{(\tilde{x}^B - \tilde{x}^i)}_{-} + \underbrace{(c_u - i)}_{+} \cdot \underbrace{(\tilde{x}^i - x^B)}_{-} \\
&< 0.
\end{aligned}$$

where $\tilde{x}^B < \bar{x}' < \tilde{x}^i$. Furthermore, $\widetilde{PV} < c_u x^B + C(x^B, \theta)$, for any $x^B \in [\tilde{x}^d, \tilde{x}^i]$ and $x^B \neq \tilde{x}^B$. Therefore, without construction uncertainties, the contractor will bid working days at $\tilde{x}^B$ in the competition stage and then choose to complete the project on time. $\square$

B.1.2 Proof of proposition 2

Recall the contractor's optimization problem in the bidding stage after plugging in the working decision function $x^{A^*}(\theta,\varepsilon)$ to response the realization of uncertainty ε for any bidding days x^B

$$\max_{p^B,x^B}\left\{p^B-\mathbb{E}\min_{x^A}\Big[(1+\varepsilon)C(x^A,\theta)+K(x^A,x^B;i,d)\Big]\right\}\Pr\Big(\text{win}\;\Big|\;S=s\Big),$$

subject to $s=p^B+c_u x^B$. First, we show that the equilibrium bidding days can be determined separately from the choice of score, and each contractor sets the bidding days according to the Equation (3.8). Suppose the contractor with type θ bids $(\tilde{p}^B,\tilde{x}^B)$ where $\tilde{x}^B\neq x^{B^*}$. By choosing the bidding days equal to x^{B^*}, we can show that the contractor can always be better-off if the bidding price is set to be $\tilde{p}^B+c_u(\tilde{x}^B-x^{B^*})$. Notice that the scores are exactly same in both cases since $\tilde{p}^B+c_u(\tilde{x}^B-x^{B^*})+c_u x^{B^*}=\tilde{p}^B+c_u\tilde{x}^B$. The difference between their expected payoff

$$\begin{aligned}
&\Big\{\pi(\tilde{p}^B+c_u(\tilde{x}^B-x^{B^*}),x^{B^*})-\pi(p^{B^*},x^{B^*})\Big\}\Pr(\text{win}\mid S=s)\\
=&\Big\{\tilde{p}^B+c_u(\tilde{x}^B-x^{B^*})-\mathbb{E}\big[C(x^{A^*},\theta,\varepsilon)-\rho\cdot(x^{B^*}-x^{A^*})\big]\\
&\;-\tilde{p}^B+\mathbb{E}\big[C(\tilde{x}^A,\theta,\varepsilon)-\rho\cdot(\tilde{x}^B-\tilde{x}^A)\big]\Big\}\Pr(\text{win}\mid S=s)\\
=&\Big\{\Big(c_u\tilde{x}^B+\mathbb{E}\big[C(\tilde{x}^A,\theta,\varepsilon)-\rho\cdot(\tilde{x}^B-\tilde{x}^A)\big]\Big)\\
&\;-\Big(c_u x^{B^*}+\mathbb{E}\big[C(x^{A^*},\theta,\varepsilon)-\rho\cdot(x^{B^*}-x^{A^*})\big]\Big)\Big\}\Pr(\text{win}\mid S=s)\\
>&0.
\end{aligned}$$

The last inequality holds following by the Equation (3.6) and the argument shown in Che (1993) that the winning probability must be positive.

Next, the optimization problem (3.6) can be solved using the established equilibrium result in standard first-price auctions literature that has established the existence and uniqueness of a symmetric monotone Bayesian Nash Equilibrium (psBNE) (see, Maskin, 1985). With the symmetric property that contractors $j \neq i$ using the identical bidding strategy $s_j = s(v_j)$, which is a strictly increasing, continuous, and differentiable function of the pseudo cost, the contractor i's winning probability $\Pr(\text{win} \mid S = s) = [1 - F_V(s^{-1}(s_i))]^{N-1}$. Then the first order condition of optimization problem (3.6) yields

$$-(N-1)(s_i^* - v_i)[1 - F_V(s^{-1}(s_i^*))]^{N-2} f_V(s^{-1}(s_i^*)) \frac{1}{s'(s^{-1}(s_i^*))} + [1 - F_V(s^{-1}(s_i^*))]^{N-1} = 0. \tag{B.7}$$

At a symmetric equilibrium, $s_i^* = s^*(v_i)$, Equation (B.7) reduces to a differential equation (here, drop the i subscript)

$$\begin{aligned} & d\big\{[1 - F_V(v)]^{N-1} s^*(v)\big\} \\ = & -(N-1)s^*(v)[1 - F_V(v)]^{N-2} f_V(v) + [1 - F_V(v)]^{N-1} s^{*'}(v) \\ = & -(N-1)v[1 - F_V(v)]^{N-2} f_V(v)]' \\ = & v d\big\{[1 - F_V(v)]^{N-1}\big\}. \end{aligned}$$

Integrating by part with boundary condition $s(\underline{v}) = 0$ yields

$$s^*(v) = v - \int_{\underline{v}}^{v} \left[\frac{1 - F_V(\tilde{v})}{1 - F_V(v)}\right]^{N-1} d\tilde{v}. \tag{B.8}$$

If θ is scalar, by the envelope theorem, $\mathrm{d}v = \mathbb{E}C_2(x^{A^*}, \theta, \varepsilon)\mathrm{d}\theta$, and it is strictly increasing in θ. We have $F_V(v) = \Pr(V(\theta) \leq v) = \Pr(\theta \leq V^{-1}(v)) = F_\Theta(V^{-1}(v)) = F_\Theta(\theta)$. Changing integration interval to $[\underline{\theta}, \theta]$ for θ

$$s^*(v) = v - \int_{\underline{\theta}}^{\theta} \mathbb{E}C_2(x^{A^*}, \theta, \varepsilon) \left[\frac{1 - F_\Theta(\tilde{\theta})}{1 - F_\Theta(\theta)}\right]^{N-1} d\tilde{\theta}. \tag{B.9}$$

Then Equation (3.7) and (3.8) can be obtained by substituting the formula of score rule and plugging the definition of pseudo cost into Equation (B.8) and (B.9) respectively. $\square$

B.1.3 Proof of proposition 3

By Theorem 1 in Torgovitsky (2015), Assumption 4 and 5 imply that the identified set for $g(\cdot,\cdot)$, denoted as $\mathcal{G}^*$ can be characterized as

$$\mathcal{G}^* \equiv \{g \in \mathcal{G} : (g^{-1}(X,V), U) \perp\!\!\!\perp W\}, \tag{B.10}$$

where $g^{-1}(x,\cdot)$ denotes the inverse of g with respect to θ, and $U \equiv F_{X|W}(\cdot)$ is the conditional rank of X. In the following proof, we focus on the case where the instrumental variable W is binary, i.e., $\mathcal{W} = \{0,1\}$. The proof for the case of continuous W is technically easier and can be found in Torgovitsky (2015).

By Assumption 5, $\theta \perp\!\!\!\perp W|U$. Also since $V|X = x, W = w$ and $X|W = w$ are assumed to be continuously distributed for all x and w, the events $[X = x, W = w]$ and $[U = F_{X|W}(x|w), W = w]$ are equivalent with each other for $x \in \mathcal{X}_w^o \equiv \text{int supp}(X|W = w)$. These two conditions together imply that if

$$F_{X|W}(x_1|w_1) = F_{X|W}(x_2|w_2) = \overline{u} \;\text{ for } x_1 \in \mathcal{X}_{w_1}^o \text{ and } x_2 \in \mathcal{X}_{w_2}^o,$$

then

$$F_{\Theta|X,W}(\theta|X = x_1, W = w_1) = F_{\Theta|X,W}(\theta|X = x_2, W = w_2) = F_{\Theta|U}(\theta|U = \overline{u}).$$

Thus, the differences between $V|X = x_1, W = w_1$ and $V|X = x_2, W = w_2$ are solely due to the direct effect of g^* on V when X is shifted from x_1 to x_2. Since the pseudo-type v is strictly increasing in θ, this direct effect can be isolated. Specifically, if $\overline{v} \in \mathcal{V}_{x_1,w_1}^o \equiv \text{int supp}(V|X = x_1, W = w_1)$, then there exists a unique $\overline{e}$ such that $\overline{v} = g^*(x_1, \overline{e})$. If the change from x_1 to x_2 does not change the conditional distribution of X given $W = w$, then from the discussion above we know the value of $g^*(x_2, \overline{e})$ can be recovered as

$$g^*(x_2, \overline{e}) = F^{-1}_{Y|X,W}(F_{Y|X,W}(\overline{v}|x_1, w_1)). \tag{B.11}$$

Following the discussion in Torgovitsky (2015), next we need to show that two things: First, $g^*(x_1, \overline{e})$ can be exogenously compared to $g^*(x, \overline{e})$ for all $x \in \mathcal{X}$. Second, $g^*(x_2, e)$ can be point-identified for a particular e of interest.

Define $I^g(x, e) = g^{-1}(x, g^*(x, e))$ as a measure of difference between g^* and any $g \in \mathcal{G}$. It can be easily verified that $I^g(x, e) = e$ if and only if $g(x, e) = g^*(x, e)$. Also by the strictly monotonicity of v in θ, $I^g(x, \cdot)$ is strictly increasing. By Assumption 4, if $I^g(x, e)$ is constant across all x, i.e., $I^g(x, e) = J^g(e)$, then $g(x, e) = g^*(x, e)$ for all $(x, \theta) \in \mathcal{X} \times \Theta$ and g^* is point-identified.

In order to show that $I^g(x, e) = J^g(e)$, suppose $g \in \mathcal{G}^*$ and define $\theta^g = g^{-1}(X, V)$. By strict monotonicity of v, we have $Q_{\Theta^g|X,W}(t|x, w) = g^{-1}(x, Q_{V|X,W}(t|x, w))$ and $Q_{V|X,W}(t|x, w) = g^*(x, Q_{\Theta|X,W}(t|x, w))$. These two conditions together imply that

$$I^g(x, Q_{\Theta|X,W}(t|x, w)) = Q_{\Theta^g|X,W}(t|x, w). \tag{B.12}$$

By the conditional independence of θ and θ^g with W, and the fact that the events $[X = x, W = w]$ and $[U = F_{X|W}(x|w), W = w]$ are equivalent with each other, the Equation B.12 can be rewritten as

$$I^g(x, Q_{\Theta|X,W}(t|x, w)) = D^g(F_{X|W}(x|w), e) \quad \text{for } x \in \mathcal{X}^o_w, e \in \Theta^o_{x,w} \tag{B.13}$$

and $D^g(F_{X|W}(x|w), e) \equiv Q_{\Theta^g|U}(F_{\Theta|U}(e|u)|u)$. From the Equation (B.13), if for all $e \in \Theta^o_{x_1,w_1}$, there exist two distinct points (x_1, w_1) and (x_2, w_2) in $\mathcal{X} \times \mathcal{W}$ such that

$$F_{X|W}(x_1|w_1) = F_{X|W}(x_2|w_2),$$

then $I^g(x_1, e) = I^g(x_2, e)$. Consequently, $I^g(x, e)$ is not a function of x and the desired point-identification result follows directly. To ensure the existence of such two points, we use a sequencing argument similar to Torgovitsky (2015). Specifically, since the bidding days can not be negative, with loss of generality we assume that $\mathcal{X} = \mathcal{X}_w = [\xi, \infty)$ with $\xi \geq 0$. Also for ease of exposition we assume that $F_{X|W}(x|1) > F_{X|W}(x|0)$ for all $x > \xi$ and $F_{X|W}(x|1) = F_{X|W}(x|0)$ for $x = \xi$, and $\Theta_{x,w} = \Theta$. Define a mapping $\pi : \mathcal{X} \mapsto \mathcal{X}$ such that

$$\pi(x) = Q_{X|W}(F_{X|W}(x|0), 1),$$

which satisfies $F_{X|W}(\pi(x)|1) = F_{X|W}(x|0)$. Pick an arbitrary point $x_0 > \xi$ and define a sequence $\{x_n\}_{n=0}^{\infty}$ such that $x_{n+1} = \pi(x_n)$. Since

$$\pi(x) = Q_{X|W}(F_{X|W}(x|0), 1) < Q_{X|W}(F_{X|W}(x|1), 1) = x$$

for all $x \in \mathcal{X}$, the sequence $\{x_n\}_{n=0}^{\infty}$ is decreasing. Therefore by Monotone Convergence Theorem and the fact that $F_{X|W}(x|1) > F_{X|W}(x|0)$ for all x except $x = \xi$, $\lim_{n\to\infty} x_n = \xi$. Figure B.5 in Appendix B.2 provides a graphic illustration of the convergence of sequence $\{x_n\}_{n=0}^{\infty}$. Then A straightforward application of the Continuous Mapping Theorem implies that

$$F_{X|W}\left(\lim_{n\to\infty} x_n|1\right) = F_{X|W}\left(\lim_{n\to\infty} x_n|0\right).$$

Since $I^g(x, e)$ is continuous and $F_{X|W}(\pi(x)|1) = F_{X|W}(x|0)$, again by Continuous Mapping Theorem,

$$I^g(x_0, e) = I^g(x_1, e) = \cdots = I^g(\xi, e). \tag{B.14}$$

Since x_0 is arbitrarily chosen, (B.14) implies that there exist two distinct points (x_0, w_0) and (ξ, w_ξ) such that $I^g(x_0, e) = I^g(\xi, e) = J^g(e)$ for all $x > \xi$ and $e \in \Theta^o$. From the previous discussion we know g^* is point-identified. $\square$

B.1.4 Additional details on the empirical application

Expression of $\hat{M}_{jk}$

$$
\begin{aligned}
\hat{M}_{jk} \equiv \; & c_{uj} x^B_{jk} - \mathbb{E}\big[(1+\varepsilon_j) C(x^A_{jk}, \hat{\theta}_{jk}) - \rho_j \cdot (x^B_{jk} - x^A_{jk})\big] \\
= \; & c_{uj} x^B_{jk} + \int_{-1}^{\varepsilon^i_j} \Big[(1+\varepsilon_j) C(x^i_{jk}, \theta_{jk}) - i_j \cdot (x^B_{jk} - x^i_{jk})\Big] dF(\varepsilon_j) \\
& \quad + \int_{\varepsilon^i_{jk}}^{\varepsilon^d_{jk}} \Big[(1+\varepsilon_j) C(x^B_{jk}, \theta_{jk})\Big] dF(\varepsilon_j) \\
& \quad + \int_{\varepsilon^d_{jk}}^{1} \Big[(1+\varepsilon_j) C(x^d_{jk}, \theta_{jk}) - d_j \cdot (x^B_{jk} - x^d_{jk})\Big] dF(\varepsilon_j).
\end{aligned}
$$

in which

$$
\begin{aligned}
C(\cdot, \theta_{jk}) &= \alpha(\cdot - x^E_j)^2 + (\beta\theta_{jk} + \gamma z_{jk})(\cdot - x^E_j) + \phi \\
x^i_{jk} &= -\frac{1}{2\alpha}\Big(\frac{i_j}{1+\varepsilon_j} + \beta\theta_{jk} + \gamma z_{jk}\Big) + x^E_j \\
x^d_{jk} &= -\frac{1}{2\alpha}\Big(\frac{d_j}{1+\varepsilon_j} + \beta\theta_{jk} + \gamma z_{jk}\Big) + x^E_j \\
\varepsilon^i_{jk} &= \; -1 - \frac{i_j}{2\alpha(x^B_{jk} - x^E_j) + \beta\theta_{jk} + \gamma z_{jk}} \\
\varepsilon^d_{jk} &= \; -1 - \frac{d_j}{2\alpha(x^B_{jk} - x^E_j) + \beta\theta_{jk} + \gamma z_{jk}} \\
i_j &= a w_j = a c_{uj} \\
d_j &= b w_j = b c_{uj}
\end{aligned}
$$

and the parameters satisfy $\alpha > 0, \beta < 0, 0 < \lambda < 1$, and $0 < a < 1 < b$.

B.2 Figures

Figure B.1: Timing of events and the contractor's decisions

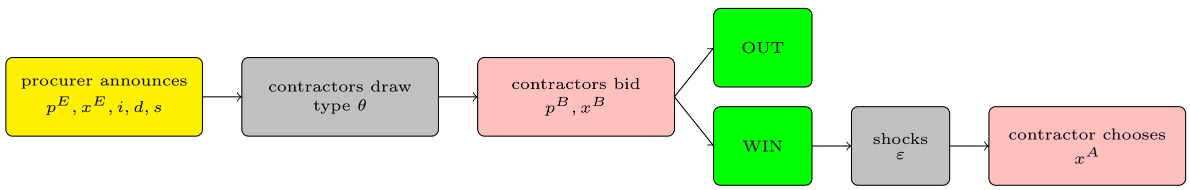


Figure B.2: Actual working days may deviate from bidding days

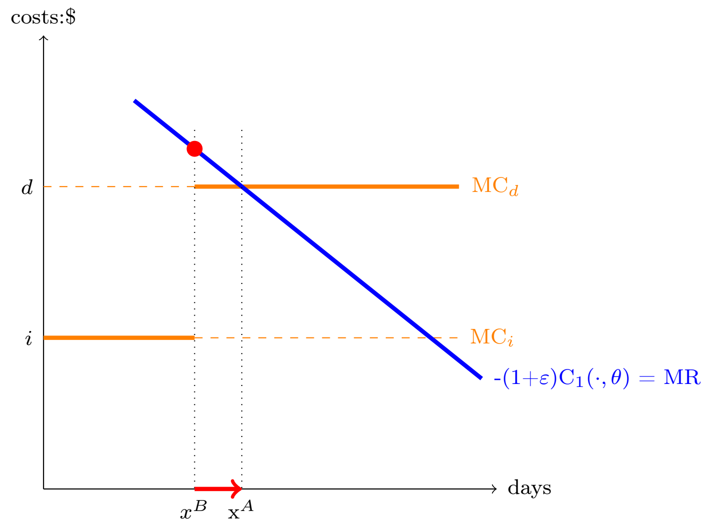


Figure B.3: Actual working days in the case of without uncertainties

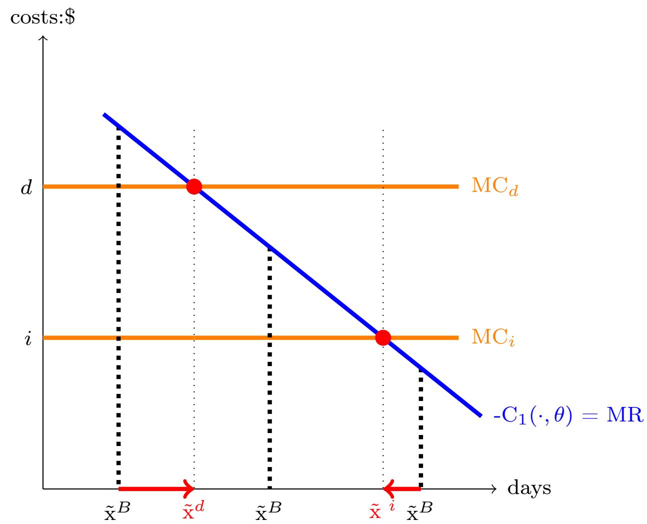
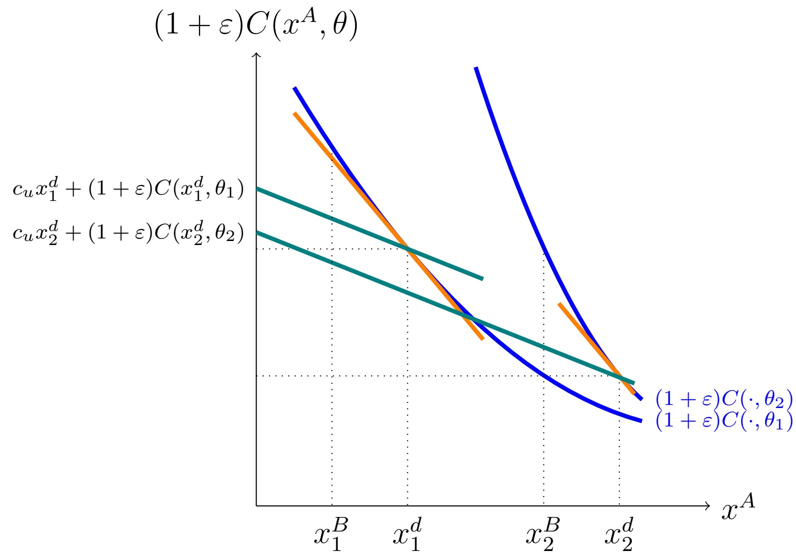
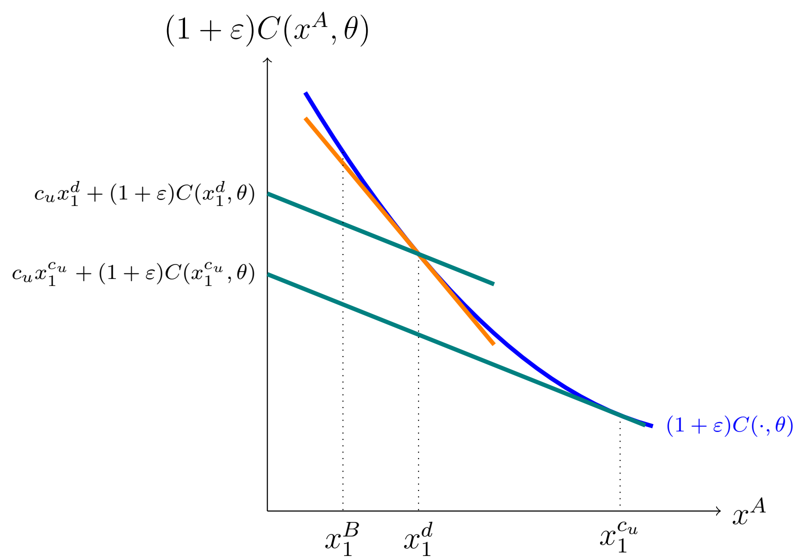


Figure B.4: Inefficiency under uncertainties



(1) Ex-ante inefficiency



(2) Ex-post inefficiency

Figure B.5: Illustration of the identification of function g^*

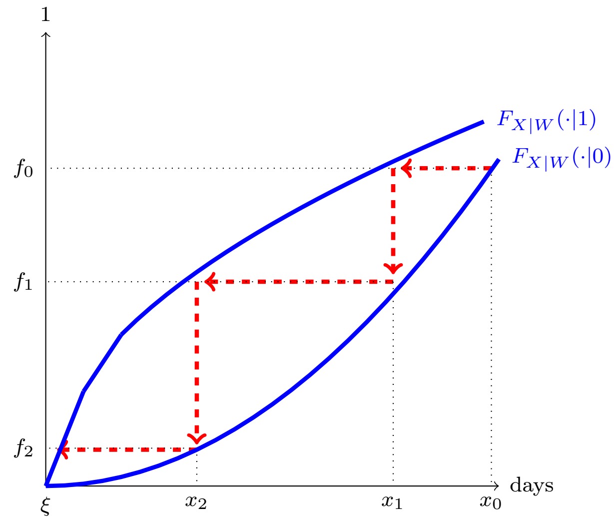


Figure B.6: Descriptive evidence of discrepancy

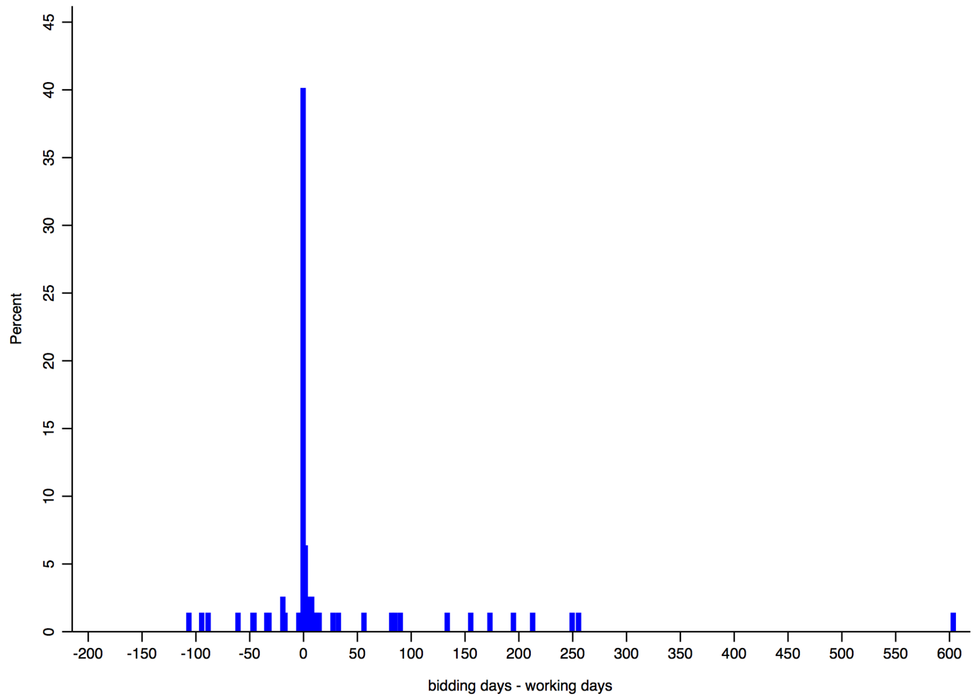
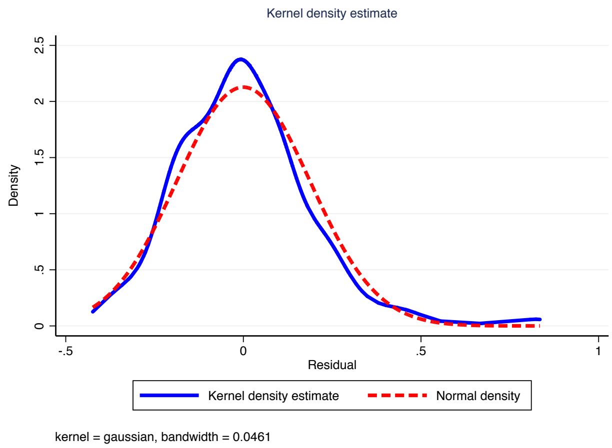
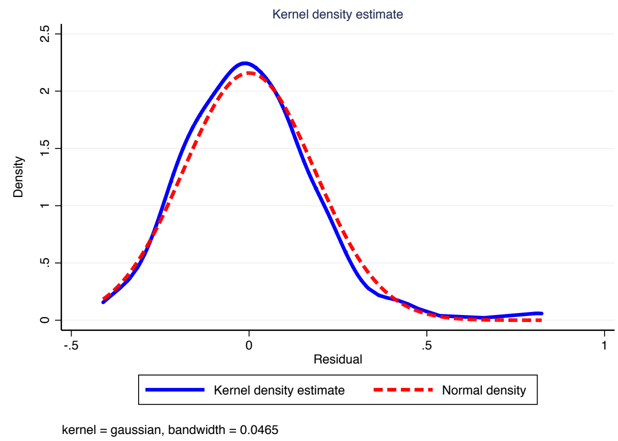


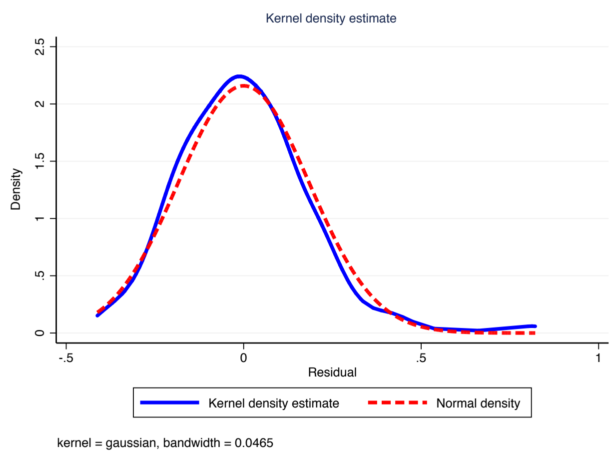
Figure B.7: Density of the residuals



(1)

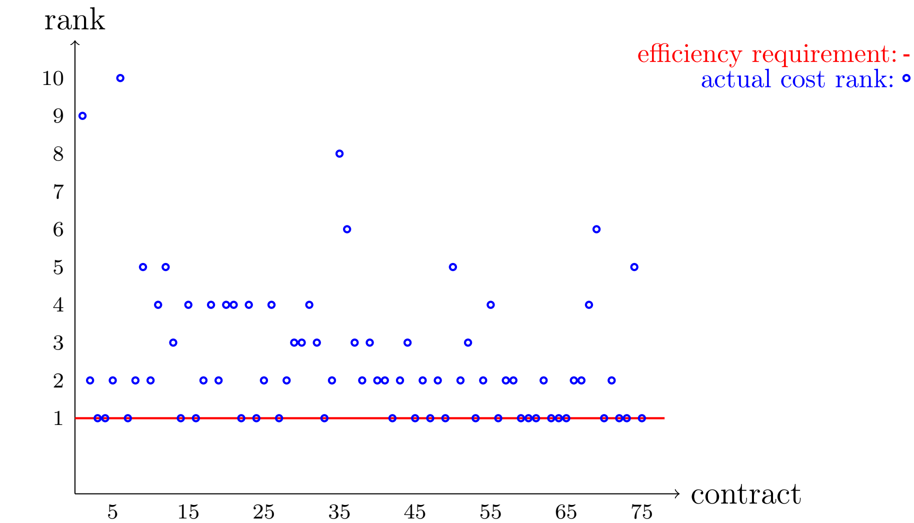


(2)

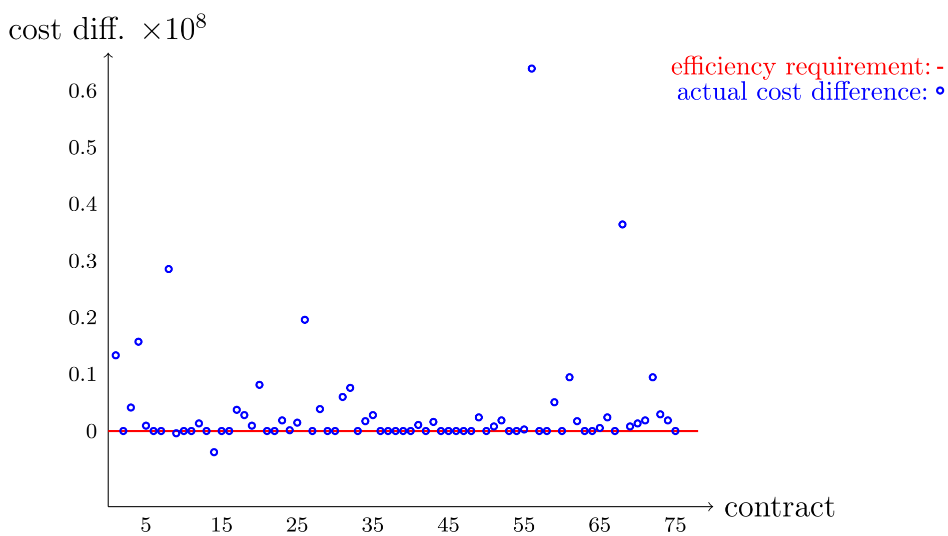


(3)

Figure B.8: Ex-ante and ex-post inefficiency

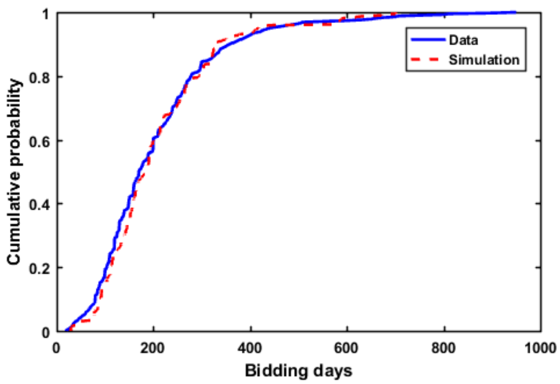


(1) Ex-ante inefficiency

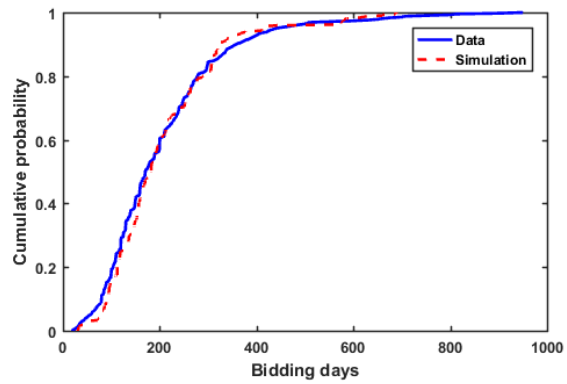


(2) Ex-post inefficiency

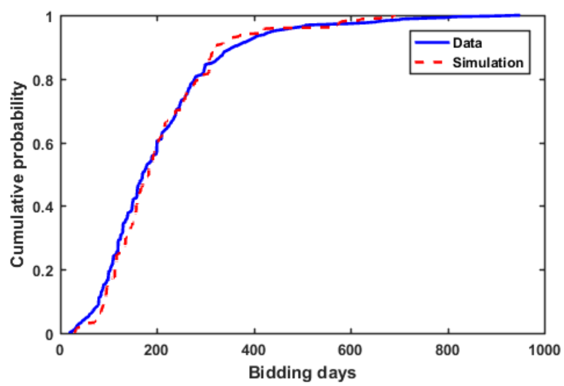
Figure B.9: Model fit: bidding days



(1)

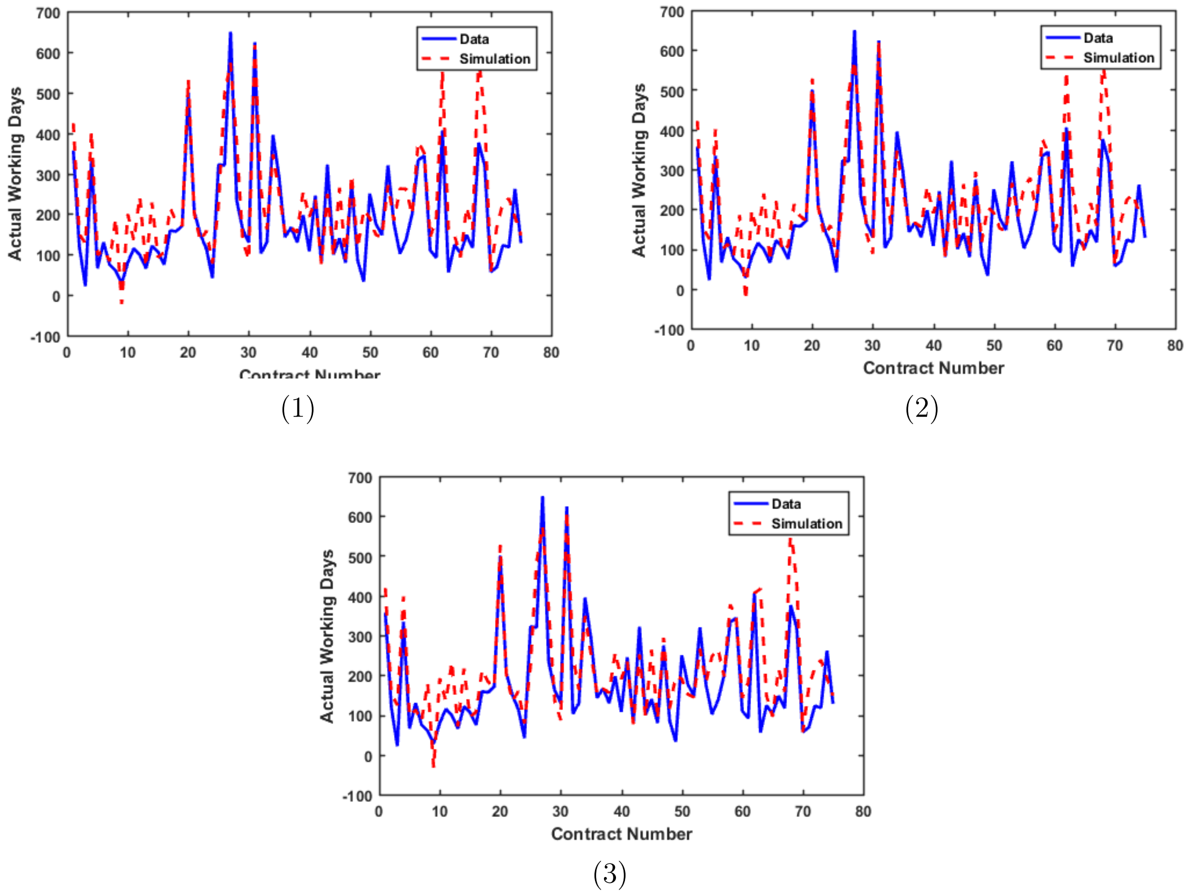


(2)



(3)

Figure B.10: Model fit: actual working days



B.3 Tables

Table B.1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
engineer's costs estimate (million \$)	21.90	29.20	0.860	198.0
engineer's days estimate	313.6	202.8	45	1000
usercost (\$)	14815	15367	1800	93985
bidding costs (million \$)	19.90	28.20	0.698	178.0
bidding days	190.1	153.4	25	813
actual working days	183.9	139.4	22	696
number of bidders	5.463	2.565	1	14
distance (miles)	65.04	127.8	1.908	802.1
firm capacity (million \$)	70.20	77.40	0	285.0
instate contractor (binary)	0.975	0.157	0	1
federal contract (binary)	0.813	0.393	0	1
daily traffic (vehicles)	117768	74062	2525	284000
lane closure fraction (%)	44.9	10.9	25.0	87.5

Table B.2: The first stage estimation results

	(1)	(2)	(3)
Constant	0.740***	0.790***	0.783***
	(0.0625)	(0.0756)	(0.0783)
Capdummy(>$50M)	-0.0584*	-0.0550*	-0.0559*
	(0.0309)	(0.0308)	(0.0310)
Distance/Estimated Bidding Days	-0.00645	-0.0299	-0.0311
	(0.0252)	(0.0413)	(0.0413)
Usercost/Estimated Bidding Days	0.0000307	0.000396	0.000405
	(0.000212)	(0.000275)	(0.000279)
In-state Contractor	0.0597	0.0151	0.0153
	(0.0548)	(0.0671)	(0.0673)
Number of Bidders	-0.0133***	-0.0133***	-0.0132***
	(0.00314)	(0.00318)	(0.00318)
Distance		0.0000547	0.0000578
		(0.000142)	(0.000141)
Usercost		-0.00000195**	-0.00000202**
		(0.000000823)	(0.000000851)
Federal Contract			0.00967
			(0.0238)
Observations	424	424	424
R^2	0.049	0.057	0.058

Notes: (a) Standard errors in parentheses; (b) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: The second stage estimation results

	(1)	(2)	(3)
Constant	1.020***	1.088***	1.090***
	(0.0511)	(0.0725)	(0.0749)
Capdummy(>$50M)	-0.0749***	-0.0767***	-0.0765***
	(0.0288)	(0.0276)	(0.0278)
Distance/Estimated Bidding Score	2696.6**	1148.0	1155.6
	(1189.9)	(1280.5)	(1307.6)
Usercost/Estimated Bidding Score	-9.450	3.744	3.505
	(21.13)	(20.03)	(19.64)
In-state Contractor	0.143***	0.107*	0.107*
	(0.0436)	(0.0598)	(0.0598)
Number of Bidders	-0.0289***	-0.0296***	-0.0296***
	(0.00284)	(0.00289)	(0.00291)
Distance		0.000123	0.000123
		(0.000114)	(0.000115)
Usercost		-0.00000274***	-0.00000273***
		(0.000000692)	(0.000000709)
Federal Contract			-0.00214
			(0.0255)
Observations	424	424	424
R^2	0.176	0.199	0.199

Notes: (a) Standard errors in parentheses; (b) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Structural estimation results

	Parameters	Estimates		
		(1)	(2)	(3)
Cost Function	α_1	202.709**	193.331***	221.303***
		(89.447)	(54.174)	(50.301)
	α_2	-204761.468***	-189668.128***	-207967.317***
		(72359.927)	(38137.009)	(36231.117)
	β_1 (distance)	-5.766**	-3.073***	-2.468***
		(2.358)	(0.875)	(0.953)
	β_2 (firm capacity)	46.485	42.343	24.871
		(1592.820)	(1512.216)	(1386.748)
	β_3 (in-state contractor)	-5387.479	-5865.766*	-3163.878
		(5593.719)	(3476.555)	(3808.598)
	β_4 (federal contract)	-33664.011***	-28416.266***	-31557.521***
		(11488.394)	(6281.580)	(6542.208)
	ϕ	528.504	761.566	183.079
		(42134.626)	(34286.920)	(189628.219)
Incentive/Disincentive	a	0.230**	0.215**	0.197**
		(0.107)	(0.092)	(0.093)
	b	8.161***	7.355***	7.698***
		(2.933)	(1.593)	(1.596)
	σ_ϵ	0.174***	0.164***	0.175***
		(0.057)	(0.029)	(0.027)

Notes: (a) Columns (1), (2) and (3) reports estimates based on the first and second stage estimates from specifications (1), (2) and (3) in Table B.2 and B.3, respectively; (b) Standard errors in parentheses are calculated using 500 bootstrap samples; (c) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Welfare analysis for the A+B mechanism

	Inefficiency Percentage			Average Welfare Loss (million $)		
	(1)	(2)	(3)	(1)	(2)	(3)
Ex-ante Inefficiency	65.33%	66.67%	66.67%	1.536	1.345	1.397
	(64.0%, 66.7%)	(65.33%, 69.33%)	(65.33%, 68.0%)	(0.674, 1.891)	(0.640, 1.744)	(0.612, 1.588)
Ex-post Inefficiency	60.0%	56.0%	53.33%	3.220	3.413	3.746
	(52.70%, 97.30%)	(51.35%, 95.95%)	(51.35%, 95.95%)	(2.093, 9.738)	(2.405, 10.037)	(2.966, 11.194)

Notes: (a) Columns (1), (2) and (3) reports inefficiency percentage and average welfare loss calculated from estimates in specifications (1), (2) and (3) in Table B.4; (b) 95% confidence intervals in parentheses are calculated using 500 bootstrap samples.

Table B.6: Model fit: regression results

(a) Bidding days

	Bidding Days in Data		
	(1)	(2)	(3)
Simulated Bidding Days	1.004***	1.028***	1.030***
	(0.0463)	(0.0474)	(0.0465)
Constant	-2.002	-5.432	-5.833
	(8.106)	(8.250)	(8.102)
Observations	424	424	424
R^2	0.784	0.783	0.786

Notes: (a) Columns (1), (2) and (3) reports estimates based on structural estimates from specifications (1), (2) and (3) in Table B.4, respectively; (b) Standard errors in parentheses; (c) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(b) Working days

	Actual Working Days in Data		
	(1)	(2)	(3)
Simulated Actual Working Days	0.834***	0.837***	0.831***
	(0.0756)	(0.0747)	(0.0900)
Constant	-2.137	-2.966	-0.920
	(14.71)	(14.62)	(16.26)
Observations	75	75	75
R^2	0.746	0.739	0.697

Notes: (a) Columns (1), (2) and (3) reports estimates based on structural estimates from specifications (1), (2) and (3) in Table B.4, respectively; (b) Standard errors in parentheses; (c) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Counterfactual analysis

	Current policy			Lane rental			A design		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Ex-ante Inefficiency Percentage	81.3%	81.5%	81.6%	18.2%	20.1%	21.9%	8.2%	7.8%	10.1%
	(73.3%, 88.0%)	(73.3%, 89.3%)	(74.7%, 88.0%)	(13.3%, 21.3%)	(16.0%, 25.3%)	(17.3%, 26.7%)	(5.3%, 10.7%)	(5.3%, 10.7%)	(6.7%, 13.3%)
Ex-ante Average Welfare Loss (million $)	3.702	3.345	3.622	2.821	2.854	3.287	0.980	0.849	1.166
	(2.848, 4.675)	(2.621, 3.943)	(2.849, 4.615)	(1.707, 3.833)	(1.959, 3.943)	(2.269, 4.500)	(0.394, 1.757)	(0.351, 1.598)	(0.547, 2.060)
Ex-post Inefficiency Percentage	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	100.0%	100.0%	100.0%
	-	-	-	-	-	-	-	-	-
Ex-post Average Welfare Loss (million $)	4.580	3.891	3.933	0.000	0.000	0.000	0.281	0.306	0.280
	(4.258, 4.948)	(3.607, 4.172)	(3.689, 4.225)	-	-	-	(0.252, 0.324)	(0.276, 0.354)	(0.250, 0.323)

Notes: (a) Counterfactual welfare analysis under different policies. Current policy is the original A+B contracting design. Lane rental is A+B design with linear incentive contracting. A design represents time incentive contracting in A design, i.e., bidders only bid price during the auction stage. (b) 95% confidence intervals in parentheses are simulated 500 times.