ESSAYS ON MARKET IMPERFECTIONS IN MACROECONOMICS AND FINANCE

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A DISSERTATION

PRESENTED TO THE FACULTY

OF PRINCETON UNIVERSITY

IN CANDIDACY FOR THE DEGREE

OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE

BY THE DEPARTMENT OF ECONOMICS

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JUNE 2017
Abstract:

Complete markets models in the spirit of Arrow and Debreu (1954) have become a central organizing framework for modern macroeconomics and finance. Implicit in this framework is that market imperfections, departures from the complete-markets assumptions, are crucial for understanding real world prices and allocations. I take this to task in this collection of essays, which investigates the quantitative impact of market imperfections in three key areas in macroeconomics and finance: asset prices, household consumption, and credit allocations.

Chapter 1 provides a quantitative explanation of the Chinese housing boom. This explanation is based on the interaction of liquidity constraints in the housing market and the transition of household wealth from a low initial condition, and is motivated by an examination of the cross-city pattern in the extent of the housing boom. A model that accommodates this explanation generates a faster-than-income increase in home prices and a speculative motive for home purchases, without the presence of bubbles, and predicts a natural plateauing of home values. This chapter serves as a quantitative example in which market imperfections generate significant effects on asset prices and household portfolio choice.

Chapter 2 carries out a test for standard life-cycle incomplete markets models where households are restricted to trading risk-free bonds. Using household micro data for the US, I provide evidence for an important unverified prediction of this class of models, that there should be large cross-sectional differences in agents’ consumption responses to long-lasting income shocks across agents of different age and wealth. Furthermore, I find that a calibrated standard life-cycle incomplete markets model predicts heterogeneity in consumption responses quantitatively similar to my empirical estimates.

Chapter 3, coauthored with Cheng Sun, studies the credit channel of monetary transmission. In particular, we take advantage of a rich data set on bank lending in
China and estimate the change in bank credit to firms following monetary policy announcements. We provide micro-level evidence that monetary policy operates through quantity as opposed to interest rates in China. Moreover, we find that across firm types, smaller and less risky businesses experience a larger increase in new loans following monetary easing. This result supports the “excess sensitivity” hypothesis of Gertler and Gilchrist (1994), but contrasts with the previous findings on the “risk-taking channel” of monetary policy, and suggests that the nature of the relationship between monetary policy and risk-taking can be complex and context-dependent.
Acknowledgments:

I am deeply indebted to my advisors, Richard Rogerson and Wei Xiong, for their endless support, encouragement, patience and invaluable insights throughout my Ph.D. studies. It has been a wonderful experience to grow as a researcher under their guidance. I will forever benefit from the rigor and clarity instilled in me by Richard Rogerson, my macro advisor, and from the curiosity and confidence instilled in me by Wei Xiong, my finance advisor.

Aside from my advisers, several professors have served an outsized role in my progress. Thanks to Markus Brunnermeier, Greg Kaplan, Atif Mian, Benjamin Moll and Motohiro Yogo, for their generosity and their extensive advice, help, and input at different stages.

In writing this thesis, I have also greatly benefited from comments and suggestions from Mark Aguiar, Maryam Farboodi, Mikhail Golosov, Valentin Haddad, Gregor Jarosch, Nobuhiro Kiyotaki, Ricardo Lagos, Adrien Matray, Ezra Oberfield, Matthew Rognlie, David Schoenherr, Jesse Schreger, Christopher Sims, Gianluca Violante, and Juan Pablo Xandri.

My gratitude also goes to my co-author Cheng Sun and my colleagues Cheng Chen, Liang Dai, Sungki Hong, Ji Huang, Zongbo Huang, John Kim, John Klopfer, Wenzhe Li, Jason Ravit and Chang Sun, for improving my research, and for the wonderful times we had in Fisher, the BCF, and the JRRB.

Special thanks to Laura Hedden, Karen Neukirchen, Jennifer Bello, Nancy Goldstein for the superb support that they always provided.

Finally, to my family: My parents, Zhongmiao Zhang and Xuefei Shi, for I would not have been here without your nurture. My father would have loved to see this. My son, Zhiyuan, for giving me new hopes and perspectives in life. And to Chenyao for being with me through thick and thin; to you, I owe the rest of my life.
To my parents
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Chapter 1

Liquidity Constraints, Transition Dynamics, and the Chinese Housing Return Premium

1.1 Introduction

Home price movements received increasing academic and public attention in recent years. The Chinese housing boom is central in this attention, in part because of its spectacular nature. Real housing prices grew 170% from 2003 to 2012 in China, more than doubling the 68% increase in the U.S. from 1997 to 2006.\footnote{The national average housing price index is from Fang et al. (2015), weighted by the value of housing in each city. The national average housing price index for the U.S. is from Case-Shiller.} Housing commands a large return premium relative to low interest rates: The average annualized price return on housing is 12.4% in real terms. In comparison, the average real return on bank savings is -0.2%, and the average mortgage interest rate is 3.5%. What made housing prices in 2003 so different from housing prices in 2012? What sustained the large gap between the return on owning housing and the return on alternative assets?
To address these two questions, I propose a novel explanation that centers on the upward transition of household wealth from a low initial condition, under liquidity constraints. This explanation contributes to the understanding of forces that underpin housing price movements. This explanation operates as follows. First, there are substantial liquidity constraints in China that limit arbitrage between different asset returns, and that tie housing prices to household wealth. Second, given that the generous former social welfare system was only phased out in late 1990s, household wealth is initially low in China in 2003, limiting housing prices to a low level relative to the net present value of future rents. But as household wealth quickly rises aided by high household savings, housing prices also quickly increase.

A key piece of motivating evidence for this explanation comes from an examination of the cross-city pattern in the extent of the housing boom. Specifically, I construct a city-level panel dataset that includes measures of price, quantity, housing value, purchasing power, and household wealth, and then document a tight comovement: increases in housing value at the city level are closely associated with increases in household wealth, whether measured with or without housing. This comovement is almost one-to-one: after I control for measures of purchasing power, the regression coefficient is around one between the growth rate of housing value and the growth rate of household wealth, whether measured with or without housing. Liquidity constraints provide a parsimonious mechanism to rationalize this strong comovement between household wealth and housing value.

To assess the quantitative plausibility of my explanation for the Chinese housing boom, I develop a rational expectations dynamic portfolio choice model with endogenous housing prices, augmented with realistic liquidity constraints and a low initial wealth. In the model, there are two goods: non-housing and housing consumption. A representative household receives endowment income in non-housing consumption, and the endowment process features risks in trend growth. The representative house-
hold also consumes both non-housing and housing consumption, and can borrow in
the form of loans, invest in a bank savings account, and buy homes. The interest rate
on loans and the bank savings account is specified exogenously. Homes, meanwhile,
yield housing consumption. The supply of homes is given by an upward-sloping supply
curve. The price of homes is determined endogenously in the model in an industry
equilibrium.

I consider the effects of two types of liquidity constraints on home price dynamics,
evolution of wealth and household portfolio compositions. I start the model at the
empirical value of the initial household wealth-to-income ratio and calibrate the model
to match the increase in the household wealth-to-income ratio. The two types of
liquidity constraints I consider are borrowing constraints and illiquidity.

Absent these liquidity constraints, the model cannot match the level of the housing
return premium and the increase in housing prices in the data, for households will
borrow and invest substantially at the beginning, bidding up prices and lowering
subsequent returns. Realistically, this borrowing and investing is neither feasible
nor optimal in the Chinese housing market: not feasible because Chinese households
face stringent borrowing constraints, and not optimal because housing is illiquid and
households need to set aside funds for emergency expenditures.

With borrowing constraints only, the model is successful in matching the level and
the trend in the housing return premium and generates 92% of the increase in housing
prices observed in the data. That said, this particular model predicts households in
China will not hold bank deposits in periods of high housing return premia, whereas
in the data, they in fact do hold substantial low-return bank deposits.

The model with borrowing constraints and illiquidity, modeled as emergency
consumption needs that must be met with liquid bank deposits, retains success in
explaining the housing return premium and the increase in housing prices and
generates a third to a half of empirical holdings of bank deposits by households. The
extended model’s inability to completely match the household portfolio echoes the finding in Telyukova (2013), and Pagel and Vardardottir (2016).

Overall, the model with borrowing constraints only offers a parsimonious account of both the high housing price return and the high premium of the housing price return relative to interest rates in China’s housing market during the sample period of 2003-2012. The model with borrowing constraints and illiquidity provides a more complete picture and matches not only the high housing price return and the high premium of housing price returns relative to interest rates, but also to some extent the observed household portfolio.

The model highlights key features of China that strongly influence the main results. The results rely on two crucial features of China: (1) a low required rate of return as a result of financial repression, and (2) the government’s releasing vast amounts of new supply into the housing market. First, the low required rate of return makes the net present value of future rents extremely high in China, and also makes liquidity constraints bind even given a seemingly high value-to-income ratio. Second, the government captures much of the price appreciation by releasing vast amounts of new supply of housing in this period. If households own all housing from the beginning, then the feedback from housing price appreciation on an initial increase in household wealth would be so strong that the transition out of liquidity constraints would be instantaneous.

Two intriguing predictions emerge from the model that help answer important unresolved questions.

First, the model in this paper helps explain the high Chinese saving rate puzzle. Specifically, the model generates an speculative motive for owning housing, and this speculative motive raises the household saving rate during the transition. Transition dynamics generate an expected appreciation on housing faster than the growth rate of income, especially at the beginning of the housing boom. Facing housing returns
that exceed expected income growth, households save with high-return housing and trade off less current consumption with more capital gains and more consumption in the future. This new explanation for high household savings in China contrasts with the negative finding in the model without the investment motive in Wang and Wen (2012).

Second, the model provides a framework for predicting the effect of a growth slowdown on the Chinese housing market. Specifically, the model predicts a rebound and a subsequent increase in housing prices following an initial drop when the growth rate of the economy has permanently slowed to zero. This pattern occurs because housing prices under liquidity constraints are tightly connected to household wealth. When the expected growth rate of income permanently drops, the target household wealth-to-income ratio increases. As aggregate household wealth converges upward toward this higher target, housing prices increase with it.

1.1.1 Literature Review

This paper makes several contributions to the literature.

First, this paper contributes to a line of literature that points to mechanisms underlying the movement of housing prices by proposing a novel mechanism that highlights the effect of household wealth accumulation on housing price movements under liquidity constraints. Some of the mechanisms already highlighted in this literature are user cost (Poterba (1984)), demographics (Mankiw and Weil (1989)), behavioral biases (Case and Shiller (1990)), geographical constraints (Glaeser et al. (2008)), and credit expansion (Favara and Imbs (2015)).

Second, this paper also contributes to a stream of literature that examines equilibrium models of housing prices. Studies in this literature include the static model in Stein (1995), and the dynamic models in Davis and Heathcote (2005), Ortalo-Magne
and Rady (2006), Kiyotaki et al. (2011), and Favilukis et al. (Forthcoming). This paper studies a dynamic equilibrium model of housing prices.

Within this literature, the closest are He et al. (2015) and Favilukis et al. (Forthcoming), both of which interprets the recent U.S. housing boom as the result of an *exogenous* relaxation of borrowing constraints. The main difference here is that my explanation relies on *endogenous* increases in liquidity through household wealth accumulation, instead of exogenous changes in constraints.

Third, this paper contributes to the growing study of liquidity constraints on asset prices and household portfolio choice. Relative to this literature, I use this paper to focus on an environment with low wealth and a large asset class (i.e., China’s housing market in transition) for which liquidity constraints are plausibly binding for the aggregate household sector and generate particularly large effects on asset prices and household portfolio choice.

Finally, this paper contributes to an emerging branch of literature on the Chinese housing boom, which includes empirical descriptive studies such as Wang and Zhang (2014), Fang et al. (2015), Wu et al. (2015), Feng and Wu (2015), Wu et al. (2016), Glaeser et al. (2016). This paper adds to the empirical descriptive studies of the Chinese housing boom by constructing a city-level panel dataset of housing values and then documenting a tight comovement between city-wide housing value and city-wide household wealth, whether measured with or without housing.

Two other papers that model the Chinese housing boom are Chen and Wen (Forthcoming) and Garriga et al. (2016). Neither paper explains the large housing return premium relative to other assets, which this paper highlights and explains.

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Chen and Wen (Forthcoming) use a rational bubble framework, in which housing is an intrinsically worthless asset and entrepreneurs hold housing with an investment motive, to explain the faster-than-income increase in housing value.
Furthermore, these two papers focus on either the store of value role or the consumption role of housing. In the model of this paper, housing is realistically modeled as both a consumption and an investment good. Finally, in sharp contrast to the bubble perspective in Chen and Wen (Forthcoming), this paper shows that a faster-than-income increase in housing value and an investment motive in holding housing arise naturally in an empirically supported and quantitatively feasible framework without bubbles.4

The remainder of this paper is organized as follows. Section 1.2 documents stylized facts that motivate the explanation in this paper. Section 1.3 illustrates the mechanism and provides relevant institutional background. Section 1.4 develops a dynamic model of the housing market for a quantitative assessment of the mechanism. Section 1.5 reports the results of the quantitative assessment. Section 1.6 discusses additional predictions of the model. Section 1.7 concludes this paper.

1.2 Stylized Facts

In this section, I document stylized facts that motivate the analysis in this paper.

1.2.1 Data Construction

To document the motivating facts, I construct a panel dataset of housing values, prices, quantities, household purchasing power, and household wealth for Chinese cities, building on the work in Fang et al. (2015), which offers a constant-quality housing price index that covers 120 cities from 2003 to 2012. To construct housing

Garriga et al. (2016) illustrate that income growth and urbanization increase housing value in Chinese cities in a model where housing is purely a consumption good. However, once investment in housing is allowed, prices no longer grow as fast as in the data.

4Also, in this paper high housing returns arise and cease endogenously, while the rational bubble in Chen and Wen (Forthcoming) cannot get started within the model (as is well known in the bubble literature, rational bubbles can never emerge within a model; they must already be present when the asset starts trading.)
values I use the perpetual inventory method, and combine information from the 2005 1% Mini Census microdata, the housing price index, and information on new home sales. I measure housing quantities in efficiency units (i.e. the ratio of housing values and housing prices). Measures of household purchasing power include disposable income, retail sales, and population; I also consider other proxies for the level of economic activities, including electricity use and the profits of industrial firms. Finally, I compute a measure of household wealth by combining city-level information on household bank deposits and mortgages with my constructed measure of housing values. This measure of household wealth in Chinese cities takes into account its two largest components—home equity and bank deposits—which together make up 80 to 90% of urban household wealth, according to calculations derived from two national household surveys that become available only around the end of my sample, the Chinese Household Finance Survey (CHFS) and the Chinese Family Panel Studies (CFPS). I describe in detail the procedure and assumptions for constructing the city-level panel dataset in Appendix A.

1.2.2 The Faster-than-Income Increase in Housing Value

The increase in housing values greatly exceeded the increase in household income. Aggregating over cities in my sample, Figure 1.1 plots the increase in housing values, housing prices, and household income. In addition to the 2.7 times growth in the real value-weighted housing price index, there is a 2.2 times growth in the quantity of housing in efficiency units. In total, real housing values increased by 5.6 times, surpassing the 3.4 times growth in real aggregate urban disposable income, which

\[ \text{values} = \frac{\text{2005 1\% Mini Census microdata}}{\text{the housing price index}} + \text{information on new home sales.} \]

\[^5\text{Data on housing value and housing quantities are scant, even in the aggregate: The National Bureau of Statistics has yet to carry out a systematic housing census. Further, the flow-of-funds tables contain no measure of housing values.}\]

\[^6\text{Data on holdings of other financial assets do not exist for the cities in my sample. Fortunately, non-bank financial markets are underdeveloped in China, and the majority of the household financial assets are in bank deposits. This measure also does not include value of personal businesses. However, this omission should not matter for checking the liquidity constraint mechanism, given that it is hard to borrow against (or cash out of) the value of personal businesses in China.}\]
already takes into account migration and population growth. Any model used to explain the Chinese housing boom needs to address the faster growth of housing values relative to household income.

1.2.3 The Large and Decreasing Housing Return Premium

The return on housing commanded a substantial premium over interest rates. Table 1.1 summarizes the average price return on housing and the average housing return premium over interest rates, weighted by the value of housing at different cities. I focus on the price return on housing \( (p_{t+1}/p_t) \) because data on the rents and imputed service flows on housing are not available. The annualized price return on housing is, on average, 12.4% in real terms. In comparison, the average real return on bank deposits, the largest financial asset class in terms of portfolio holdings by households, is -0.2%, and the average mortgage interest rate is 3.5%.
Table 1.1: Housing Return Premium over Risk-Free Rates, National Weighted Average, 2003–2012

<table>
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<tr>
<th></th>
<th>Mean</th>
<th>Standard deviation</th>
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<tr>
<td>Real housing price appreciation</td>
<td>12.4%</td>
<td>11.6%</td>
</tr>
<tr>
<td>Real interest rate on deposits</td>
<td>-0.2%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Real interest rate on mortgages</td>
<td>3.5%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Excess return over deposit rate</td>
<td>12.6%</td>
<td>11.4%</td>
</tr>
<tr>
<td>Excess return over mortgage rate</td>
<td>8.9%</td>
<td>11.4%</td>
</tr>
</tbody>
</table>

Note: This table summarizes the average price return on housing and the average housing return premium over interest rates, weighted by the value of housing in different cities. Standard error of sample mean in parentheses. Nobs = 9.
A high return premium is puzzling, in part because an investor can gain much by reallocating funds to the asset with a higher return, especially if the volatility of the return premium is not very large compared to the average return premium. This is indeed the case here, as the Sharpe ratio (the ratio between the average return and the standard deviation) of housing relative to the deposit rate is 110%, and the Sharpe ratio of housing relative to the mortgage rate is 78%.

Moreover, during the period 2003–2012, the housing return premium seems to trend downward over time. A downward trend in the housing return premium could suggest some kind of convergence between the return on housing and interest rates. The average housing return premium over the deposit rate during 2003–2007 is 18.2%, while the average housing return premium over the deposit rate during 2007–2012 is 8.1% (excluding 2007–2008, the year of the global financial crisis, the average is 11.4% during 2008–2012).

The downward trend is graphically illustrated in Figure 1.2, in which the dashed line is the actual realization of the housing return premium over the deposit rate, and the solid line is an estimated linear trend of the housing return premium.
Table 1.2: Statistical Significance of the Trend in the Housing Return Premium

<table>
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<th>Sample</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>Time Trend</td>
<td>-0.0124***</td>
<td>-0.0031**</td>
<td>-0.0063***</td>
<td>-0.0162**</td>
<td>-0.0187***</td>
<td>-0.0098***</td>
</tr>
<tr>
<td>Observations</td>
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<td>792</td>
<td>792</td>
<td>36</td>
<td>234</td>
<td>621</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.064</td>
<td>0.004</td>
<td>0.013</td>
<td>0.052</td>
<td>0.143</td>
<td>0.043</td>
</tr>
<tr>
<td>Number of Cities</td>
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<td>99</td>
<td>99</td>
<td>4</td>
<td>26</td>
<td>69</td>
</tr>
</tbody>
</table>

Note: In this table I regress the city-level housing return premium over the deposit interest rate on a linear time trend. Column (1) reports the result for the full sample, which indicates a significant and large downward trend in the housing return premium. Columns (2) and (3) report robustness of the downward trend to removing the first or the last year of observations, respectively. Columns (4)-(6) report robustness of the downward trend for cities in each tier in China. Standard errors are clustered at the city level. *** indicates significance at the 1% level. ** indicates significance at the 5% level.

To check further on the statistical significance of the trend in the housing return premium, Table 1.2 reports the results of regressing the city-level housing return premium over the deposit interest rate on a linear time trend. The linear time trend is statistically significant. The statistical significance of the downward time trend is robust when I remove the first year or the last year of observations and is also robust for cities of all tiers in China. 7

---

7The decrease in the housing return premium raises some doubts about explanations based on risks of a bubble collapsing. To the extent that such an explanation involves a bubble that is growing, households’ exposure to the risk of a bubble collapsing should increase over time, which should be expected to increase the housing return premium over time.
1.2.4 Across Cities: A One-to-One Relationship Between Value of Housing and Household Wealth, Including or Excluding Housing

The cities that experienced the largest housing boom in 2003–2012 tend to be the cities that experiences the largest increase in household wealth, whether including or excluding housing.

To more fully understand the mechanism that underlies the Chinese housing boom, I explore the characteristics of Chinese cities that experienced the largest housing boom in 2003–2012. In particular, I use the city panel dataset to estimate the following panel regressions:

\[ \log(p_{it}) = \alpha_i + \beta \log(wealth_{it}) + \gamma_1 \log(income_{it}) + \gamma_2 \log(population_{it}) + \varepsilon_{it}, \]

(1.1)

\[ \log(p_{it}q_{it}) = \alpha_i + \beta \log(wealth_{it}) + \gamma_1 \log(income_{it}) + \gamma_2 \log(population_{it}) + \varepsilon_{it}. \]

(1.2)

I include city fixed effects in the panel regressions to focus on the movement of both the housing market and the right-hand side variables. To make sure the coefficient on \( \log(wealth) \) is not just due to regressing housing on housing, I use two different wealth measures: wealth including housing and wealth excluding housing (which is simply household bank savings).

Table 1.3 reports the results of the panel regressions. The results suggest that cities that have seen the biggest increases in housing prices and in housing value also tend to be cities that have seen the biggest increase in household wealth, whether that measure of wealth includes or excludes housing. The magnitude of the association is large: a one percent higher growth in household wealth is associated with around a half percent higher price appreciation in housing and a one percent higher increase
Table 1.3: City-Level Panel Regression Results

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) Log(Home Price Index)</th>
<th>(2) Log(Total Value of Housing)</th>
<th>(3) Log(Total Value of Housing)</th>
<th>(4) Log(Total Value of Housing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Wealth</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Measures (Including Housing)</td>
<td>0.604***</td>
<td>0.492***</td>
<td>1.107***</td>
<td>1.062***</td>
</tr>
<tr>
<td>Net Worth</td>
<td>-0.0656</td>
<td>0.265***</td>
<td>0.0574</td>
<td>0.524***</td>
</tr>
<tr>
<td>Bank Deposits</td>
<td>-0.0301</td>
<td>0.128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>990</td>
<td>990</td>
<td>990</td>
<td>990</td>
</tr>
<tr>
<td>Adjusted-$R^2$</td>
<td>0.94</td>
<td>0.89</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Number of Cities</td>
<td>99</td>
<td>99</td>
<td>99</td>
<td>99</td>
</tr>
<tr>
<td>City FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

Note: This table reports results of the following city panel regressions:

$\log(p_{it}) = \alpha_i + \beta \log(wealth_{it}) + \gamma_1 \log(income_{it}) + \gamma_2 \log(population_{it}) + \varepsilon_{it},$

$\log(p_{it}q_{it}) = \alpha_i + \beta \log(wealth_{it}) + \gamma_1 \log(income_{it}) + \gamma_2 \log(population_{it}) + \varepsilon_{it}.$

The regressions include city fixed effects. All variables are deflated by the consumer price index at the province level. Two different wealth measures are used: wealth including housing and wealth excluding housing (which is simply household bank savings). Standard errors are clustered at the province level. *** indicates significance at the 1% level.

in the overall value of homes. The coefficients on log(wealth) are similar whether I include or exclude housing from household wealth, suggesting that the estimated tight relationship is not due simply to regressing housing on housing.

Figure 1.3 graphically illustrates the tight relationship between increases in the total value of homes and increases in household (total or non-housing) wealth. Log housing value and log household wealth are first regressed on log income and log population. I take the regression residuals and plot the 2003–2012 growth rate in (residual) housing value over the growth rate in (residual) household wealth, including
Figure 1.3: Growth in the Overall Value of Homes Is Positively Associated with Growth in Household (Non-Housing) Wealth

(a) Wealth measure including housing. Slope of fitted line: 1.16.

(b) Wealth measure excluding housing. Slope of fitted line: 0.97.

Note: This figure plots the 2003-2012 growth rate in (residual) housing value over the growth rate in (residual) household wealth. The residuals are constructed by regressing log housing value and log household wealth on log income and log population. Left: Wealth including housing. Right: Wealth excluding housing (which is simply household bank savings).

or excluding housing. Again, the slope of the fitted line representing the association between increases in the total value of homes and increases in household wealth is similar and close to one, whether I include or exclude housing from household wealth.

The one-to-one association between increases in the total value of homes and increases in household (total or non-housing) wealth is quite robust. Specifically, it is robust to: (1) additional proxies of purchasing power and of levels of economic activity as controls in the panel regressions (e.g., retail sales, electricity use, profit of industrial firms), which address to some extent omitted variable bias; (2) exclusion of three Northeastern provinces that are reputed to be more prone to statistical manipulation; and (3) inclusion of time fixed effects in the panel regressions, which further addresses the concern that coefficients could be picking up common aggregate time trends shared by the housing market and the right-hand-side variables.
1.2.5 Summary of Stylized Facts

To summarize, I document four stylized facts on the Chinese housing boom:

Fact 1: A substantial housing return premium exists, for the price return on housing is much higher than interest rates on financial saving and borrowing.

Fact 2: The housing return premium trends downward over time.

Fact 3: The increase in housing prices and housing quantities are both large. The increase in the total value of housing in the Chinese housing boom is beyond the increase in purchasing power during 2003–2012.

Fact 4: The increase in the total value of housing at the city level is associated one-to-one with the increase in household wealth, whether including or excluding housing.

1.3 Proposed Mechanism and Institutional Background

Liquidity constraints together with an upward transition in Chinese household wealth provide a mechanism that potentially explains the large increase in housing prices, the large and declining housing return premium, and the faster-than-income-growth increase in housing values that is linked one-to-one with the increase in household wealth.

The mechanism operates as follows. Liquidity constraints and low initial household wealth limit housing demand, thereby generating the low housing prices in 2003. Subsequently, household savings from low initial household wealth generate a transitional increase in household wealth, which lifts housing demand, driving up both housing prices and quantities. The increase in housing demand is amplified by a feedback loop through which appreciation of existing housing generated by the initial increase in household wealth leads to a further increase in household wealth, and so on.
This mechanism explains the aforementioned stylized facts naturally. For example, liquidity constraints, especially in the form of constraints on borrowing, provide a natural explanation for Fact 1 (level of housing return premium) and Fact 4 (cross-city association). Liquidity constraints create a tight connection between Chinese household wealth and how much Chinese households can invest in housing, which accounts for Fact 4. Liquidity constraints also create limits to arbitrage between the high return on housing and the low return on financial saving and borrowing, which accounts for Fact 1.

Further, when liquidity constraints are initially binding, a large increase in Chinese household wealth, coupled with a growth rate of wealth faster than the growth rate of income, can explain Fact 2 (downward trend in housing return premium) and Fact 3 (increase in housing value beyond increase in income). Housing values also increase one-to-one with household wealth under the binding liquidity constraints, at a rate faster than the growth rate of income, which accounts for Fact 3. Finally, the increase in household wealth also makes binding liquidity constraints less tight, reducing limits to arbitrage between the high return on housing and the low return on financial saving and borrowing, which accounts for Fact 2.

This explanation is consistent with, and relies upon, institutional details in the Chinese housing market and with the dynamics of Chinese household wealth. In this section, I show that (1) institutional details in China indeed imply influential liquidity constraints, and (2) Chinese household wealth indeed saw a large transitional increase from a low initial value in the sample period aided by both savings and capital gains, following the phasing out of the generous old social welfare system.

1.3.1 Liquidity Constraints for Chinese Home Buyers

Liquidity constraints limit the amount of funds in the Chinese housing market relative to household wealth. When household wealth is low, liquidity constraints lower the
price of housing below the net present value of future rents. I focus on two types of liquidity constraints most relevant to Chinese households: borrowing constraints and illiquidity. I describe the extent to which they are relevant for Chinese households in their housing investment.

**Borrowing Constraints**

Constraints on borrowing limit the amount of funds a household can invest in housing relative to the amount of household wealth. Access to borrowing for the purchase of homes in China is limited to mortgage borrowing, and mortgage regulations are very stringent in China. The regulatory constraints on mortgage borrowing are multifaceted, impacting a wide range of potential borrowers. I describe some of these constraints here:

- **Downpayment constraint:** The China Banking Regulatory Commission (CBRC) imposes a minimum downpayment ratio on mortgage borrowings in China. For most of the period I study, the minimum downpayment ratio is 30%. In comparison, zero downpayment mortgages are widespread during the U.S. housing boom.

- **Payment-to-income constraint:** The CBRC also constrains mortgage borrowing relative to the current income of borrowers, as a monthly mortgage payment cannot exceed 50% of the monthly income of the borrower at the time of borrowing. Although payment-to-income constraints are not unique to China, the high expected income growth in China makes the constraint especially restrictive in China, given that the constraint is set in terms of current income, which is potentially very low relative to future income.

- **Inflexible repayment schedule:** The CBRC requires mortgage loans to be repaid in either equal installments of principal, or in equal installments of principal and
interest. This makes it impossible to avoid the payment-to-income constraint by choosing an increasing repayment schedule.

- Limits on refinancing: Mortgage refinancing, the act of taking out a new mortgage to pay off the old one, is not allowed. On a similar note, mortgage maturity cannot be extended through refinancing.

- Limits on borrowing for investment homes: Rich households that want to buy multiple homes face more stringent borrowing constraints. The minimum downpayment ratio for a second home is substantially higher than that for a first home. Mortgage borrowing on a third home and beyond are not allowed.

- Difficulty in borrowing against older homes: Many homes constructed before the sample period, especially those built by work units as in-kind benefits, are poor quality and have been improperly maintained, and some times without proper titles. As a result, banks are unwilling to extend credit on those homes and imposes stringent building age requirements.

In sum, substantial constraints on mortgage borrowing limit the amount of funds that Chinese households can use in addition to household wealth for the purchase of housing.

**Illiquidity**

Illiquidity of housing reduces the fraction of household wealth that households are willing to invest in housing in the presence of emergent expenditure needs. Extraction of wealth in housing is costly in terms of time costs and/or pecuniary costs, and households would optimally withhold some wealth in liquid assets that are more easy to access, even if the return on housing is much higher than the return on liquid assets. Illiquidity of housing then, plays a more important role if there are strong
needs for expenditures that cannot be covered by regular paychecks. I describe some types of such expenditures that seem to be important for Chinese households:

- **Out-of-pocket medical expenses**: Out-of-pocket medical expenses are not billed, and must be paid on the spot in Chinese hospitals during the day or week of treatment. This creates a strong incentive for households to withhold some wealth in liquid assets rather than in high-return housing. The magnitude of out-of-pocket medical expenses is large. In the CFPS microdata in 2012, the share of out-of-pocket medical expenses relative to total annual expenditures is, on average, 11%, with a highly skewed distribution: for 3% of the households, out-of-pocket medical expenses exceed 55% of total annual expenditures; for 1% of the households, out-of-pocket medical expenses exceed 83% of total annual expenditures.

- **Expenses during unemployment**: Unemployment benefits in China are regulated to be below the local minimum wage, which is already set at a very low level and can in no way be considered a living wage. Since the extraction of housing wealth remains costly, this creates another incentive to withhold some wealth in liquid assets instead of in high-return housing.

In sum, the chance of large emergency expenditures conditional on illiquidity of housing further limits the amount of funds relative to household wealth that Chinese households will use for the purchase of housing.

### 1.3.2 Upward Transition in Chinese Household Wealth

Since liquidity constraints create a tight link between household wealth and the amount of funds in the housing market, a large increase in Chinese household wealth can drive large increases in housing prices and quantities by increasing the amount of
funds in the constrained housing market. This feeds back to the increase in household wealth through the appreciation of households’ existing housing holdings.

Chinese household wealth was arguably still in transition in 2003. Unique institutional features of the Chinese economic system at that time are important factors that help explain this transition. China used to be a communist/socialist economy in which personal property had a minimal role. A generous social welfare system provided housing, healthcare, education, and pension benefits. Households needed minimal savings. The economic reform, which started in 1978, initially did not touch the social welfare system, until budgetary pressures forced social welfare reform in the 1990s, which greatly cut education and health benefits, eliminated in-kind housing benefits, and lowered the pension replacement rate. Household saving rates rose from 10% to 20% in the 1990s and continued to increase in the 2000s. Still, household wealth was only 3.2 times disposable income in the initial sample year of 2003, which is 30% lower than the lowest wealth-to-income ratio among advanced economies studied in Piketty and Zucman (2014).

From 2003 to 2012, the data show a large upward movement in household wealth, both in levels and in the wealth-to-income ratio. Adjusted for inflation, household wealth increased 5.2 times. Half of the increase in wealth levels comes from two types of saving: saving in financial assets and the purchase of new homes. Another half of the increase in wealth levels comes from the appreciation on both existing housing owned prior to 2003, and new housing bought since 2003. The wealth-to-income ratio increased from 3.2 to 5.2 (Figure 1.4), reaching the range of wealth-to-income ratios studied in Piketty and Zucman (2014).

In sum, following the phasing out of the generous former social welfare system, Chinese household wealth indeed saw a large transitional increase from a low initial value in the sample period.
Figure 1.4: Left: Increase in Level of Real Household Wealth and Composition of the Increase. Right: Increase in Household Wealth-To-Income Ratio

Note: The left panel plots the increase in the level of urban aggregate household wealth, deflated by the consumer price index. The bottom part represents household wealth in 2003. The middle part represents new household savings, including saving in financial assets and the purchase of new homes. The top part represents the appreciation on both existing housing owned prior to 2003 and new housing bought since 2003.

The right panel plots the increase in the urban household wealth-to-income ratio. The income measure is disposable income. The dashed line plots the time series of the urban household wealth-to-income ratio. The solid line plots smoothed values obtained by applying the Hodrick-Prescott filter.
1.4 Model and Equilibrium

In this section, I develop a model of China’s housing market during 2003–2012 that emphasizes the effects of transition dynamics in the aggregate household wealth from a low initial condition, under liquidity constraints, on the Chinese housing market. Features of this model are specially designed to capture key aspects of the reality in China.

The model is a dynamic portfolio choice model with two goods, non-housing and housing, and three assets: housing, bank deposits, and mortgages, which capture the largest asset classes accessed by urban Chinese households. There is a representative family consisting of a continuum of member households that receive endowment income in the non-housing good. The endowment process features a high trend growth state and a low trend growth state, which captures the high trend growth in China and the long-run risks of a slowdown in fundamentals.

Housing is priced in an industry equilibrium, with households as the demand side. A member household in the representative family is potentially constrained with respect to the amount of funds it can use to purchase housing, as reflected by the level of household wealth combined with liquidity constraints. I consider two types of liquidity constraints: borrowing constraints and illiquidity. Borrowing constraints are modeled as exogenous constraints on mortgage borrowing. Illiquidity is modeled via a within-period shock that creates a need for emergency expenditures for some member households of the representative family; because this need cannot be financed with wealth in housing, it must be financed with bank deposits.

To focus on transition dynamics in household wealth under liquidity constraints, the supply side of the housing market is intentionally stylized, and is modeled as an upward-sloping supply curve in the stock of housing; as such, the total quantity of housing supplied increases with the price of housing.
1.4.1 Model

Endowment

There is a representative family with a continuum of member households. For the moment, all member households are identical, and the subscript indexing households within the representative family is suppressed for clarity.

Households receive a stochastic endowment $y_t$ of the non-housing good at the beginning of the period. The endowment process $y_t$ captures the high trend growth in China, as well as a stark long-run risk of future slowdown. Specifically:

$$y_t = \Gamma_t z_t.$$  \hspace{1cm} (1.3)

The first component of $y_t$, $\Gamma_t$ represents the cumulative product of past trend growth $\{g_0, \ldots, g_t\}$:

$$\Gamma_t = g_t \Gamma_{t-1} = \Pi_{s=0}^{t} g_t.$$  \hspace{1cm} (1.4)

In particular, trend growth $g_t$ follows a two-state Markov chain:

$$g_t \sim \text{Markov}( \begin{bmatrix} g_H \\ g_L \end{bmatrix}, \begin{bmatrix} 1 - \pi_g & \pi_g \\ 0 & 1 \end{bmatrix}).$$  \hspace{1cm} (1.5)

The Markov chain for trend growth $g_t$ in (1.5) implies that the slowdown is permanent: the economy never emerges from low growth once a slowdown occurs. In Section 6, I exploit this specification of the long-run trend growth risk to explore the model’s prediction for housing price dynamics when a slowdown occurs.

The second component $z_t$ represents a stationary shock to the stochastic endowment process that captures short run risks in fundamentals, and is modeled as another

\footnote{The nature of change in trend growth is likely to be less discrete in reality. Here I keep the specification of $g_t$ simple, to make the model results easier to interpret; that said, I will consider richer growth processes in future research.}
two-state Markov chain:

\[ z_t \sim \text{Markov} \left( \begin{bmatrix} z_H \\ z_L \end{bmatrix} \right), \left[ \begin{array}{cc} 1 - \pi_z & \pi_z \\ \pi_z & 1 - \pi_z \end{array} \right] \). \]  

(1.6)

Markets

The non-housing good is the numeraire. There is a market for ownership of housing. Housing ownership trades at price \( p_t \). Housing is divisible and depreciates at rate \( \delta \) each period.

Households have access to risk-free saving \( a_t \) in bank deposits and risk-free borrowing \( b_t \) in mortgages (subject to borrowing constraints) at exogenous interest rates. The interest rate on bank deposits is \( R_a \). The interest rate on mortgages is \( R_b \). I choose the setup with exogenous interest rates to reflect the complex nature of the monetary system in China.\(^9\)

Liquidity Constraints

The first type of liquidity constraint that households face is an exogenous borrowing constraint on mortgages. In Section 5, the model’s dynamics on housing prices and wealth dynamics is mostly driven by liquidity constraints of this type. Specifically, the constraint on mortgage borrowing is the following:

\[ b_t \leq \psi(p_t) \cdot p_t h_t. \]  

(1.7)

The function \( \psi(\cdot) \) is increasing in \( p_t \), and bounded by \( \bar{\psi} \). The upper bound \( \bar{\psi} \) reflects a standard loan-to-value (LTV) constraint on collateral borrowing against housing values.\(^{10}\) The ratio \( \psi(\cdot)/\bar{\psi} \) reflects that some urban homes in China cannot be

\(^9\)Credit quotas and monetary aggregate targeting more closely describe the monetary system in China than market clearing in the interest rate margin. See Chen et al. (2016) for a discussion.

\(^{10}\)The constraint on mortgage borrowing (1.7) does not explicitly reflect the no-refinancing restriction in Chinese housing. Modeling long-term mortgages in the model is an extension that I am currently working on.
borrowed against in mortgages. Many older homes, especially those built by work units as in-kind benefits, are poor quality and have been improperly maintained. As a result, banks are unwilling to extend credit on those homes. Newer commercial homes are more easily borrowed against; therefore, the fraction of homes that can be borrowed against increases over time. However, modeling $\psi$ as a function of time adds time as a state variable. To economize on the number of state variables, I model $\psi(\cdot)$ as a function of the price of housing, which increases over time in the data.

The second type of liquidity constraint that households face is illiquidity. Illiquidity is modeled via within-period emergency consumption shocks, where the amount of emergency consumption to be made is limited by the amount of bank deposits.

The emergency consumption shock is realized within each period. At the start of each period and before the within-period emergency consumption shocks are realized, each member household receives endowments $y_t$, and the representative family decides the portfolio choices $h_t$, $a_t$, $b_t$, and the amount of normal consumption $c^n_t$ for each member household.

When the within-period emergency consumption shock is realized, with a probability of $\pi$ a member household has to make an emergency consumption $c^m_t$. Emergency consumption can be obtained by drawing down bank deposits $a_t$:

$$c^m_t \leq a_t. \tag{1.8}$$

Equation (1.8) is the liquidity constraint due to illiquidity in this model, or in other words the emergency consumption constraint. A member household hit with the emergency consumption shock consumes emergency consumption $c^m_t$ subject to (1.8), and also consumes normal consumption $c^n_t$. A member household not hit with the emergency consumption shock consumes normal consumption $c^n_t$ only. After consumption and at the end of each period, the representative family pools resources
— deposits $a_t - \pi c^m_t$, loans $b_t$, and housing $h_t$ — and any within-period heterogeneity is resolved.

The motivation for adding illiquidity as another type of liquidity constraint is to create another incentive for Chinese households in the model to limit their investments in housing in face of high housing price returns. Because emergency consumption is valued and the amount of emergency consumption is limited by the amount of bank deposits, some of household wealth will be optimally set aside in bank deposits and not in housing.

Another motivation for adding illiquidity is that I observe households holding substantial bank deposits in their respective portfolios during the Chinese housing boom despite large return differences. Illiquidity via the emergency consumption constraint, then, is a channel to generate bank deposit holdings in the model.

**Household Preferences**

The representative family chooses $c^n_t$, $c^m_t$, $h_t$ and $a_t$ to maximize the following Epstein-Zin-Weil utility function for each member household:

$$V_t = \left\{ \left[ E_{t-} \left( c_t^{1-\theta} h_t^\theta \right)^{1-\gamma} \right]^{\frac{1-\frac{1}{\sigma}}{1-\gamma}} + \beta \left[ E_t (V_{t+1})^{1-\gamma} \right]^{\frac{1-\frac{1}{\sigma}}{1-\gamma}} \right\}^{\frac{\sigma}{\sigma - 1}}$$

(1.9)

where $E_{t-}$ denotes the expectation at the beginning of period $t$, before the within-period emergency consumption shock is realized, and where $c_t$ is an aggregator over normal and emergency consumption that depends on the realization of the emergency consumption shock:

$$c_t = \begin{cases} 
  c^n_t & \text{with prob } 1 - \pi \\
  (c^n_t)^{1-\kappa} (c^m_t)^\kappa & \text{with prob } \pi
\end{cases}$$

(1.10)
I choose an Epstein-Zin-Weil utility function so that the model may more easily capture high household savings in China during a period of high growth by separating the elasticity of intertemporal substitution and the relative risk aversion.\(^{11}\)

In the special case that \(\gamma = 1/\sigma\), the utility function of the member household reduces to

\[
V_0 = \begin{cases} 
E_0 \sum_{t=0}^{\infty} \beta^t \left( c_{t}^{1-\theta} h_{t}^{\theta} \right)^{1-\gamma} & \text{if } \gamma \neq 1, \\
E_0 \sum_{t=0}^{\infty} \beta^t \log \left( c_{t}^{1-\theta} h_{t}^{\theta} \right) & \text{if } \gamma = 1,
\end{cases}
\]  
(1.11)

where \(c_t\) is again the aggregator over normal and emergency consumption given by (1.10).

**Household Budget Constraint**

The member household start with an initial wealth \(w_0\). The member households have to obey the following liquidity constraints

\[
\begin{align*}
\text{Household Budget Constraint} & \\
& \text{The member household start with an initial wealth } w_0. \text{ The member households have} \\
& \text{to obey the following liquidity constraints} \\
& \quad b_t \leq \psi(p_t) \cdot p_t h_t, \\
& \quad c_{t}^{m} \leq a_t,
\end{align*}
\]

and the following budget constraints:

\[
\begin{align*}
& c_{t}^{n} + a_t + p_t h_t - b_t \leq y_t + w_t, \\
& w_{t+1} = R_a(a_t - \pi c_{t}^{m}) + p_{t+1}(1 - \delta)h_t - R_b b_t.
\end{align*}
\]  
(1.12)  
(1.13)

Also, \(a_t, b_t\) cannot be negative, implying that households cannot have negative deposits or negative mortgages. This setup reflects that some households in China hold deposits and borrow in mortgages simultaneously.

\(^{11}\)See Choi et al. (Forthcoming) for a discussion.
Budget constraints (1.12) and (1.13) illustrate the relationship between dynamics in household wealth and housing choices. When households save by forgoing consumption, household wealth $w_t$ is expected to grow. When household wealth $w_t$ grows, households have more resources to buy housing $h_t$ for investment and consumption, given liquidity constraints (1.7) and (1.8). The choice of housing $h_t$ further influences the dynamics of household wealth $w_t$ through changes in the price of housing $p_t$ over time.

**Housing Supply**

To focus on liquidity constraints and transition dynamics in household wealth, the supply side of the housing market is intentionally stylized and modeled as an upward-sloping supply curve, governed by a single parameter $\varepsilon$:

$$H^S = \bar{H} \cdot p^\varepsilon.$$  \hspace{1cm} (1.14)

The parameter $\varepsilon$ has a clear interpretation as the price elasticity of housing supply (in terms of the stock of housing). This helps disciplining the parameter $\varepsilon$ in the quantitative analysis.

Furthermore, this parsimonious specification of the housing supply curve provides a good fit of the aggregate price and quantity of housing in the data. 1.14 indicates a linear fit between $\log(H_t)$ and $\log(p_t)$. Figure 1.5 plots $\log(H_t)$ and $\log(p_t)$ in the aggregate data, as measured by efficiency units of housing and the housing price index, respectively. The R-squared statistic of the linear regression of $\log(H_t)$ on $\log(p_t)$ is 97.8%.

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Figure 1.5: Linear Fit of $\log(H_t)$ and $\log(p_t)$ in the Aggregate Data

$\log(H_t) = -0.04 + 0.85*** \log(p_t)$  $R^2 = 97.8$

Note: This figure plots $\log(H_t)$ and $\log(p_t)$ in the aggregate data, as measured by efficiency units of housing and the housing price index, respectively. The solid line plots a linear fit of $\log(H_t)$ on $\log(p_t)$ estimated in the regression $\log(H_t) = \beta_0 + \beta_1 \log(p_t) + u_t$. The plotted equation reports the regression coefficients and the R-squared statistic. *** indicates significance at the 1% level.

1.4.2 Equilibrium

In this subsection, I restate the household maximization problem recursively and define the recursive equilibrium of the model.

The state vector of the household maximization problem consists of individual household wealth $w$, aggregate household wealth $W$, trend aggregate income $\Gamma$, and transitory aggregate income state $z$. Aggregate housing $H^S$ is not a state variable because it is a function of aggregate household wealth $W$; this is due to the homogeneity of the housing supply curve (1.14).

The household maximization problem, stated recursively, is:

$$V(w; W, \Gamma, z) = \max_{c^n, c^h, h, a, b} \left\{ \left[ E_\pi \left( c^{1-\theta} h^{\theta} \right)^{1-\gamma} \right]^{1-\frac{1}{1-\gamma}} + \beta \left[ E \left( V(w'; W', \Gamma', z')^{1-\gamma} \right) \right]^{1-\frac{1}{\sigma-1}} \right\}$$  \hspace{1cm} (1.15)
where $E_-$ denotes the expectation at the beginning of period, before the within-period emergency consumption shock is realized, and where

\[
c = \begin{cases} 
  c^n & \text{with prob } 1 - \pi \\
  (c^n)^{1-\kappa} (c^m)^{\kappa} & \text{with prob } \pi 
\end{cases}
\]

subject to

\[
c^n + a + p(W, \Gamma, z) \cdot h - b \leq \Gamma \cdot z + w, \quad (1.16) \\
w' = R_a(a - \pi c^m) + p(W', \Gamma', z') \cdot (1 - \delta) \cdot h - R_b b, \quad (1.17) \\
0 \leq a, b, \quad (1.18) \\
b \leq \psi(p(W, \Gamma, z)) \cdot p(W, \Gamma, Z) \cdot h, \quad (1.19) \\
c^m \leq a. \quad (1.20)
\]

The final two constraints, (1.19) and (1.20), represent the two types of liquidity constraints: borrowing constraints and illiquidity. Equations (1.16) and (1.17) represent the evolution of household wealth.

**Recursive Equilibrium**

Definition: A *recursive equilibrium* of the model is a housing price function $p(W, \Gamma, z)$, a value function $V(w; W, \Gamma, z)$, a collection of policy functions $c^m(w; W, \Gamma, z)$, $c^n(w; W, \Gamma, z)$, $a(w; W, \Gamma, z)$, $b(w; W, \Gamma, z)$, and $h(w; W, \Gamma, z)$, and a law of motion for aggregate household wealth $W' = G(W, \Gamma, z, \Gamma', z')$ such that:\footnote{The law of motion for aggregate household wealth $W' = G(W, \Gamma, z, \Gamma', z')$ depends on the next period states $\Gamma'$ and $z'$, because the next period price of the aggregate holding of housing depends on the next period states, which becomes clear in equilibrium condition (1.22).}

**a. [Optimality]:** Given the housing price function and the law of motion for aggregate household wealth, the value function and the policy functions solve the household maximization problem defined by (1.15).
b. **[Housing market clearing]**: The housing market clears at each state:

\[ h(W; W, \Gamma, z) = H_0 \cdot p(W, \Gamma, z)^\varepsilon. \]  
(1.21)

c. **[Consistency]**: Given policy functions and the housing price function, \( W' = G(W, \Gamma, z, \Gamma', z') \) solves the transition equation of aggregate household wealth:

\[ W' = R_a(a(W; W, \Gamma, z) - \pi c^m(W; W, \Gamma, z)) - R_b(W; W, \Gamma, z) + p(W', \Gamma', z')(1 - \delta)h(W; W, \Gamma, Z). \]  
(1.22)

The stochastic processes for \( \Gamma, z \), the housing price function \( p(W, \Gamma, z) \), and the law of motion for aggregate household wealth \( W' = G(W, \Gamma, z, \Gamma', z') \), collectively determine the joint dynamics of housing prices and household wealth in the equilibrium of the model.

**Balanced Growth Path**

I choose to define a balance growth path equilibrium as an equilibrium in which the growth rates of the model variables are constant, assuming realizations of the endowment shocks are kept constant. On a balanced growth path with trend endowment growth rate \( g_t \), income \( y_t \), non-housing consumption \( c_t \) (both normal consumption \( c^t_n \) and emergency consumption \( c^m_t \)), and wealth \( w_t \) all grow at the rate \( g_t \). The price of housing \( p_t \) grows at rate \( g_t^{1/(1 + \varepsilon)} \). The quantity of housing \( h_t \) grows at rate \( g_t^{\varepsilon/(1 - \varepsilon)} \).

The behavior on the balanced growth path in this model underscores the importance of transition dynamics in my explanation of the Chinese housing boom. The observed faster-than-income growth in housing values is not possible on the balanced growth path of the model, as the value of housing \( p_t h_t \) shares the growth rate of income \( g_t \). In other words, the price of housing in the model, absent transition dynamics, cannot grow at the empirical observed rate, given that the quantity of housing also
increased substantially in this period. It is possible however, as I show later, if the transition from low initial household wealth is taken into account.

**Numerical Solution**

I solve for the recursive equilibrium of the model numerically. As with the case for models with trend growth, the recursive equilibrium in this model needs to be normalized before it can be numerically solved;\(^{13}\) I detail the normalization procedure in Appendix B. The solution to the model is invariant to the choice of normalization.

The model also belongs to the class of equilibrium models with occasionally binding constraints, which can involve highly non-linear equilibrium functions. Therefore, I solve this model by using globally accurate methods to ensure accuracy with respect to the effects of transition dynamics of aggregate household wealth on the housing market. The numerical procedure is otherwise standard. Starting with a guess for the housing price function and for the law of motion for aggregate household wealth, I use value function iteration to solve the household maximization problem. I then update the guess for the housing price function and for the law of motion for aggregate household wealth, until convergence is achieved.

### 1.5 Quantitative Assessment

The model described in the previous section is designed to assess the quantitative plausibility of my explanation for the Chinese housing boom; I base my explanation on the upward transition of Chinese household wealth from a low initial condition, under liquidity constraints. In this section, I perform a quantitative assessment. Specifically, I parameterize versions of the model with (1) a borrowing constraint only, (2) a borrowing constraint plus illiquidity, and (3) no liquidity constraints. I start the model at the empirical value of the initial urban household wealth-to-income

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\(^{13}\)See Aguiar and Gopinath (2007) for an example.
ratio, and then calibrate the model to match the increase in the urban household wealth-to-income ratio. Finally, I check the model’s fit with respect to the dynamics of housing prices, with respect to the dynamics of aggregate household wealth, and with respect to household portfolio compositions.

1.5.1 Parameterization

Table 1.4 presents the values for externally determined parameters.

The model period is chosen to be annual to match the frequency of empirical observations. I choose the endowment growth rate in the high growth state to be 12.5%, which is the sample average real growth rate of urban aggregate income. This growth rate reflects the contribution of migration into urban areas, and therefore is higher than the contemporaneous growth rate of national income. I choose the probability of a slowdown to be 0.05, implying an expected duration of 20 years of high growth conditional on being in the high-growth state. I also choose the endowment growth rate in the low growth rate to be zero, motivated by the experience of Japan following its high growth period. Finally, I follow Curtis and Mark (2010) and choose parameters for the process for transitory endowment fluctuations to match a standard deviation of 1.7% and a persistence of 0.6.

The housing depreciation rate is set to 1.5% a year, consistent with my construction of housing value and quantities in the city-level panel dataset. I discipline the housing supply elasticity $\varepsilon$ by using the empirical ratio of the percentage growth in housing quantity relative to the percentage growth in housing price. The resulting value is 0.67.

My model features an endowment process that is subject to shocks to long-run growth. Following the long-run risk literature, I set the elasticity of intertemporal substitution (EIS) to be 1.5, the value in Bansal and Yaron (2004). The value of the relative risk aversion (RRA) equals 2. This is the preferred value in the portfolio
choice model with housing in Campbell and Cocco (2015), and also in the model of liquid asset holding in Telyukova (2013). I set the housing weight in consumption to 0.20, the weight used in the official CPI basket in China.

Real interest rates are set to 0% for bank deposits and 4% for mortgages, the sample average values for the period. The low real interest rate on bank deposits, despite high growth in China, reflects financial repression. The maximum loan-to-value ratio $\bar{\psi}$ is set to be 30%, taking into account regulatory constraints in the Chinese mortgage market, as I discussed in Section 3. Of note, the maximum loan-to-value ratio in the model does not correspond to the maximum loan-to-value ratio for first-time home buyers at origination (70%). The maximum loan-to-value ratio in the model takes into account the additional regulatory restrictions that include age restrictions, payment to income, payment schedule restrictions, and no-borrowing restrictions on investment homes. Not all homes can be borrowed against in mortgages in the China, because many homes constructed before the sample period—especially those built by work units as in-kind benefits—are poor quality and have been improperly maintained.

I discipline the evolution of the fraction of collateralizeable homes using an annual survey of home types in Beijing from 2003–2012, and take collateralizeable homes to be commercially constructed homes. The fraction then increases from 1.3% in 2003 to 35% in 2012. I set the functional form of the fraction of collateralizeable homes in the model, $\psi(\cdot)/\bar{\psi}$, to be $\max(0, 1 - \lambda_1/p^{\lambda_2})$, with $\lambda_1 > 0$, $\lambda_2 > 1$, and choose $\lambda_1$, $\lambda_2$ to match the empirical fraction in 2003 and 2012 at the empirical level of housing prices.

For the emergency consumption shock, I parameterize it to have a probability of 3% that gives rise to a desired emergency consumption share of 83% ($\pi = 0.03$, $\kappa = 0.83$). To place this number in perspective, 1 percent of urban households in the CFPS 2012 microdata experience medical expenditures that exceeds 83% of total consumption expenditures. The parameters thus assume a 2% chance of other types
of emergency consumption needs (e.g., unemployment) that require a substantial holding of financial assets.

After choosing the externally determined parameters, I calibrate the model with (1) a borrowing constraint only, and (2) a borrowing constraint plus illiquidity (i.e., emergency consumption shocks) to match the observed evolution in Chinese urban households’ wealth-to-income ratio.

I start the model in 2003 to reflect institutional developments in the Chinese housing market. In 2003, the State Council announced in Document No. 18 that market provision of housing would be the main form of housing in China, and 2003 marked the first year of a full-fledged housing market in which most households would expect to participate in.\footnote{Work units provided urban housing as in-kind benefits until the housing benefit was phased out in 1998 and existing homes were essentially transferred to occupants. Between 1998 and 2003, the government stance on housing was that government-supplied “affordable housing” (priced at construction costs with purchase rights allocated through a housing lottery) would be the main supply of housing.}

I start the model at the empirical initial household wealth-to-income ratio of 3.2 in 2003, and calibrate the discount factor $\beta$, which controls the target wealth-to-income ratio (holding other parameters fixed), so as to hit the empirical household wealth-to-income ratio of 5.2 in 2012, assuming income growth $g_t$ and the transitory income state $z_t$ take high realizations during this high growth period in China.

The resulting value of the discount factor $\beta$ is 0.991 for the model with a borrowing constraint only, and 0.99 for the model with a borrowing constraint plus illiquidity. A large calibrated discount factor implies that Chinese households were relatively patient. This value of the discount factor is not unusual for studies that aim to match patterns in wealth accumulation in China and is lower than the calibrated value in the influential study of Song et al. (2011).
Table 1.4: Parameters Determined Outside the Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[g_H, g_L]$</td>
<td>Endowment growth</td>
<td>$[1.125, 1.00]$</td>
<td>Growth of urban agg. income</td>
</tr>
<tr>
<td>$Pr(g_H</td>
<td>g_L)$</td>
<td></td>
<td>0.05</td>
</tr>
<tr>
<td>$[z_H, z_L]$</td>
<td>Endowment fluctuations</td>
<td>$[0.979, 1.021]$</td>
<td>$s.e.(z) = 0.017$ in Curtis and Mark (2010)</td>
</tr>
<tr>
<td>$Pr(z_H</td>
<td>z_L)$</td>
<td></td>
<td>0.2</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Housing depreciation</td>
<td>0.015</td>
<td>Housing land lease up in 70 years</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Supply elasticity</td>
<td>0.67</td>
<td>Sample $%\Delta H/%\Delta p$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>EIS</td>
<td>1.5</td>
<td>Bansal and Yaron (2004)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>RRA</td>
<td>2</td>
<td>Campbell and Cocco (2015), Telyukova (2013)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Housing weight</td>
<td>0.20</td>
<td>CPI basket</td>
</tr>
<tr>
<td>$(R_a, R_b)$</td>
<td>Interest rates</td>
<td>(0%, 4%)</td>
<td>Sample average</td>
</tr>
<tr>
<td>$\bar{\psi}$</td>
<td>LTV constraint</td>
<td>30%</td>
<td>Regulatory constraints in Chinese mortgage market</td>
</tr>
<tr>
<td>$\psi(\cdot)/\bar{\psi}$</td>
<td>Fraction of collateralizeable homes</td>
<td>1.3% at $p_{2003}^{data}$</td>
<td>Housing survey in Beijing (2003–2012)</td>
</tr>
<tr>
<td>$\pi$</td>
<td>Prob(emergency cons.)</td>
<td>0.03</td>
<td>1% chance tail medical event + assumed 2% other events</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Emergency cons. weight</td>
<td>0.83</td>
<td>Tail event medical expenditure in CFPS microdata</td>
</tr>
<tr>
<td>$w_0$</td>
<td>Initial W/Y</td>
<td>3.2</td>
<td>Sample initial value</td>
</tr>
</tbody>
</table>


1.5.2 Main Result

Now, let me turn to my main result. Panel (a) of Figure 1.6 reports the fit of the model for the housing return premium, the difference between the price return on housing, and the deposit interest rate. Overall, the model quite successfully explains the high level and the declining trend in the housing return premium as well as the large increase in housing prices.

Both the version of the model with a borrowing constraint only and the version of the model with a borrowing constraint plus illiquidity generate an average of an 11.1 percentage points housing return premium from 2003 to 2012, which explains 89% of the empirical average housing return premium of 12.5 percentage points.

The model also generates a declining trend in the housing return premium: the housing return premium is 24 percentage points in 2003-2004, and then gradually declines to 8 percentage points in 2011-2012. The magnitude of this decline is similar to that in the linear trend of the observed housing return premium, which decreases from 22 percentage points in 2003-2004, to 5 percentage points in 2011-2012.

The borrowing constraint drives virtually all housing price dynamics in the model. The time path of the housing return premium in the version of the model with borrowing constraints only is almost indistinguishable from that in the version of the model with borrowing constraints plus illiquidity.

Both versions of the model generate an increase of 156% in the level of housing prices, which accounts for 92% of the observed increase in the weighted average housing price index from 2003 to 2012.

The model produces a time path of the housing return premium that is much smoother relative to the data in panel (a) of Figure 1.6. The model calculation assumed that the realization of the transitory aggregate income state $z$, which is a two-state Markov chain in the model, is always in the high state. In panel (b) of Figure 1.6, I therefore assess the extent to which transitory fluctuations in aggregate
Figure 1.6: Model Versus Observed Housing Return Premium
(a) (b)

Note: This figure plots the main results of the model. Panel (a) reports the model’s fit in the housing return premium, assuming high realizations in $g$ and $z$. Versions of the model with liquidity constraints generate time series of the housing return premium that are similar to the data in terms of the level and the trend. Panel (b) reports the extent to which model fluctuations in $z$ can generate the volatility of the housing return premium in the data.

income can generate the volatility of the housing return premium in the data. In the version of the model with a borrowing constraint only, I set the transitory aggregate income state $z$ to be in the high state in years during which the observed housing return premium is above the smoothed trend (2004, 2007, 2009, 2011), and in the low state in all remaining years.

The result is the red dashed line in panel (b) of Figure 1.6. Transitory fluctuations in aggregate income generate a qualitatively similar pattern in the realized housing return premium as that in the data. Quantitatively, transitory fluctuations in aggregate income generate an 1.2% standard deviation in the realized housing return premium relative to trend, which is too low compared to a 9.6% standard deviation relative to trend in the data. Introducing temporary fluctuations in housing supply, which the model currently abstracts from, can potentially increase the volatility of housing prices and housing price return in the model.
I now turn to the model’s fit along other dimensions. In Figure 1.7, I report the model’s fit with respect to the transition dynamics of the household wealth-to-income ratio.

The model generates a transition in household wealth that occurs too fast when compared to the data, in that the increase in the wealth-to-income ratio in the model is too concentrated in the first half of the ten-year period of 2003–2012. This occurs because households in the model take great advantage of the high price return on housing in the initial years, saving more and using new savings to buy up housing at the beginning. As they enjoy the benefits of appreciation, the wealth-to-income ratio quickly rises.

The overly fast increase in the wealth-to-income ratio in the model may reflect the ways in which the model abstracts from indivisibility in housing and heterogeneity in household wealth. If homes have a minimum size, then households with low wealth may not reap the benefit of high housing appreciation in the initial years of the period.
Indivisibility also affects households with higher wealth, as they need to accumulate downpayment savings in between purchases of multiple homes. If the indivisibility delays the purchase of homes for a large fraction of households in the initial years of the period, then the increase in the wealth-to-income ratio will be slower, as well as closer to the data.

In Table 1.5, I report the model’s prediction on portfolio moments. Some distance exists between portfolio holdings in the model and in the data. The model generates too much holding of housing relative to wealth. That said, the holding of housing relative to wealth increases over time, both in the model and in the data.

The version of the model with a borrowing constraint only generates no deposit holdings, as expected. The version of the the model with a borrowing constraint and illiquidity generates substantial deposit holdings, despite large differences between the high return on housing and the low return on deposits.

However, the level of deposit holdings in the model does not fully rationalize the data. For example, in 2012, the model generates about a third of the deposit holdings in the data. Boosting relative risk aversion from the baseline value of 2 to a higher value of 5 (the preferred value in the portfolio choice model with housing in Cocco (2005)) increases deposit holdings in 2012 to about a half of the data, as households become more averse to low consumption in emergencies.

In the model, deposit holdings are lower in 2003 relative to later years, because the higher housing return premium in 2003 reduces households’ willingness to hold deposits.

The model’s abstraction from housing indivisibility could again be one reason for the tension between the model and data with respect to deposit holdings. In terms of indivisibility, households must save sufficiently for the housing downpayment, which might take some time, before they can purchase a first home or additional homes. This might explain the high level of deposits in the data. This might also explain why
Table 1.5: Model Versus Observed Household Portfolio

<table>
<thead>
<tr>
<th></th>
<th>2003</th>
<th>2012</th>
<th>2003</th>
<th>2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>0.68</td>
<td>0.86</td>
<td>0.42</td>
<td>0.23</td>
</tr>
<tr>
<td>Borrowing constraints only</td>
<td>1.10</td>
<td>1.16</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Borrowing constraints</td>
<td>1.05</td>
<td>1.08</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>+ Illiquidity</td>
<td>1.05</td>
<td>1.08</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>Borrowing constraints</td>
<td>1.01</td>
<td>1.02</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>+ Illiquidity (RRA = 5)</td>
<td>1.01</td>
<td>1.02</td>
<td>0.07</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Note: This table reports the model’s fit on portfolio moments. The model generates too much holding of housing relative to wealth, though the holding of housing relative to wealth increases over time, both in the model and in the data. For 2012, the model generates about a third to a half of the deposit holdings in the data.
deposit holdings decrease over time, as more households have accumulated sufficient
downpayment savings with the passage of time.

1.6 Additional Predictions and Discussion

In the previous section, I showed that the model based on the upward transition
of aggregate household wealth under liquidity constraints, taking into account key
features of the reality in China, is capable of rationalizing the stylized facts on both
housing price growth and on the housing return premium in the Chinese housing
boom. In this section, I show that although the model is stylized in certain dimensions,
the model generates interesting additional predictions regarding the saving rate of
Chinese households, as well as the fate of the Chinese housing market in the event of
an economic slowdown. I also use the Singaporean housing market as an example of
the applicability of my explanation to other emerging housing markets.

1.6.1 High Unconstrained Value of Housing

There is substantial debate in the popular press over whether housing values in China
are too high. However, the question is not well-defined in the absence of specified
benchmark values of housing against which housing values in the Chinese market can
be compared.

The model in this paper provides a framework for thinking about the benchmark
value of housing. Specifically, I define two versions of the benchmark value of housing.

The first is the value of housing in the model without liquidity constraints, with
household wealth at the 2012 empirical level (to hold fixed income effects of household
wealth) and with borrowing interest rates at $R_b = 4\%$. This is the value of housing
in the model to a hypothetical unconstrained borrower, whose required rate of return
is $R_b$. In the model, this value is around six times the household income in the
The second versions of the benchmark value of housing differs from the first by setting the both interest rates in the model at $R_a = 0\%$. This is the value of housing in the model to a hypothetical unconstrained deep-pocketed saver, whose required rate of return is $R_a$. In the model, this value is fifteen times the household income in the high-growth state, and around eight times the household income in the low-growth state.

Both versions of the benchmark value of housing are very high, which points to two key aspects of the reality in China: (1) high expected growth and (2) low financial asset returns as the required rate of return. The intuition follows from the Gordon growth formula $p = d/(r - g)$, which suggests that if a required return $r$ is low and dividend growth $g$ is high, then price will naturally be high.\textsuperscript{15} In the deep-pocketed saver’s evaluation, especially, the asset of housing is attractive even at a seemingly high price because the alternative is the zero percent saving interest rate.

1.6.2 High Household Saving Rate

The puzzlingly high saving rate of Chinese households has spurred active research in recent years. Put succinctly, Chinese households save tremendously, even though income growth is very high and the return on financial assets is very low.

The model in this paper generates a high household saving rate. In the model, households save as much as 55 percent of income in 2003. The saving rate gradually declines to 30 percent in 2012.

The housing market boom contributes to this high saving rate through a speculative motive: Transition dynamics generates an expected appreciation on housing that is faster than the growth rate of income, especially in 2003. Facing housing returns

\textsuperscript{15} See Song (2014) for a similar discussion.
that exceeds expected income growth, household save in high-return housing and trade off less current consumption for more capital gains and more future consumption.

There is another target savings motive created by liquidity constraints: with constraints on borrowing, households have a target wealth-to-income ratio, and in the face of high income growth, they need to save at a high rate just to maintain the wealth-to-income ratio.

### 1.6.3 Housing Rebound After Permanent Slowdown in Income Growth

Should a permanent growth slowdown impact the Chinese housing market, conventional arguments based on fundamentals conclude that the price of housing will drop permanently.

My model suggests otherwise. In fact, the model as parameterized in the previous section, predicts that the price of housing in China will have only a temporary dip if a permanent growth slowdown occurs and will then rise above the peak level prior to slowdown, even with the extreme assumption that income does not grow at all after the slowdown.

In Figure 1.8, I report the evolution of the model economy in the hypothetical event of a permanent growth slowdown in the year 2013 (panel (a)), after which there is no income growth ($g_t$ transitions from $g_H$ to $g_L$, and the growth rate of real income post-slowdown is $g_L = 0$).

As shown in panel (b) of Figure 1.8, the price of housing initially drops by 9.7% upon impact of the permanent slowdown shock, but subsequently rebounds and eventually surpasses the pre-slowdown peak. Again, this assumes the absence of any income growth after the slowdown. What, then, explains this paradoxical rebound
Figure 1.8: Model Predictions in the Event of a Permanent Slowdown

Note: This figure reports the predicted evolution of the model economy in the hypothetical event of a permanent growth slowdown in year 2013 (panel (a)), after which there is no income growth ($g_t$ transitions from $g_H$ to $g_L$), and the growth rate of real income post slowdown is $g_L = 0$.)
and growth in the price of housing after a permanent worsening of fundamentals, absent any further growth in income?

The explanation is that: (1) the liquidity constraints are still binding and affect the price of housing after the slowdown, and (2) households are willing to maintain higher wealth in the low-growth state after the slowdown compared to in the high-growth state. A higher level of household wealth in the low-growth state increases the price of housing. In the low-growth state, lower expected income growth, taking as given the same subjective discount rate and the same financial asset returns, generates a higher target wealth-to-income ratio. The target level of aggregate household wealth increases, given that the slowdown shock did not change the level of income. The price of housing increases as liquidity constraints tie the movement in the price of housing to the movement in the aggregate household wealth, and the aggregate household wealth increases toward the now higher target, as shown in panel (c) of Figure 1.8.

The model also predicts leverage on housing will drop permanently in the event of a slowdown, as shown in panel (d) of Figure 1.8, because return on housing no longer justifies borrowing in the event of a slowdown. However, savers in the model still put any additional savings into housing, absent emergency consumption needs, because the overall return on housing—including the service flow—is still higher than the saving interest rate of zero percent.

Finally, the model predicts a decline in the household saving rate after the slowdown, as shown in panel (e) of Figure 1.8. This is mostly because less savings are required to maintain the target wealth-to-income ratio with zero growth in income.

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16Holding the financial asset returns the same makes sense because interest rates are already low in the high-growth state, a result of financial repression and the underdevelopment of non-bank financial markets.
Figure 1.9: Singaporean Housing Market from 1990 to 2004

*Note:* This figure plots the Singapore HDB Resale Price Index from 1990 to 2004. Following reforms in 1989–1993 that expanded purchase eligibility in Singapore’s HDB resale market, the price of HDB flats rose, and returns on housing were much higher than on other assets. It took about five years for the price of HDB flats to reach the end level.

1.6.4 The Case of Singapore

The Singaporean housing market provides another example that illustrates the relevance of the explanation in this paper.

The Singaporean housing market is dominated by HDB flats: apartments built by the Housing Development Board. There are strong restrictions in the market for HDB flats, such as income ceilings, citizenship requirements, family size restrictions, and financing restrictions. There was a significant reform that removed some of these restrictions in the HDB flat market during 1989-1993.

Before 1989, only citizens who did not own other residential properties in households with a minimum size of two persons, and with household incomes below the HDB-established income ceiling were eligible to purchase new or used HDB flats (Phang (2007)).
In 1989, the income ceiling was removed from the resale market for HDB flats. In addition, permanent residents were allowed to purchase used HDB flats. Beginning in 1991, single citizens above the age of 35 were allowed to purchase used HDB flats. In 1993, household balances in compulsory savings accounts became eligible for mortgage repayments.

In Figure 1.9, I shows the movements in the Singaporean HDB resale price index following reforms in the resale market of HDB flats. The prices rose, eventually settled at around 240% of its 1990 level. The return on housing was much higher than on other assets. It took about five years for the price of HDB flats to reach its final level.

In my explanation, the large increase in the price of housing in the Singaporean market was due to prices being initially very low in 1989; the high housing return premium in Singapore persisted for several years because Singaporean citizens and permanent residents required time to build up their wealth and realize the final level of the higher price of housing.

1.7 Conclusion

Transition dynamics of household wealth from a low initial condition, coupled with liquidity constraints, offer a novel framework for understanding the puzzling housing boom in China. Calibrated to match the empirical transition in household wealth in China, this framework explains the large increase in housing prices, explains the substantial and declining housing return premium relative to interest rates, generates an investment motive in holding housing, helps rationalize the high household saving rate, and offers unique predictions about the effect of a growth slowdown on the Chinese housing market.

This framework can potentially be applied to other emerging housing markets in which households have low wealth and in which there are liquidity constraints (e.g.,
Japan, beginning in the late 1950s). As more less-developed countries begin similar transition processes, this framework may be useful for understanding similar dynamics in less expected places, such as some of the quickly urbanizing African nations.

This framework offers substantial room for future research. For example, the framework can benefit from introducing additional important frictions in the housing market. Indivisibility is one such friction: Homes are an investment of substantial size, and downpayment savings for large home purchases may rationalize both substantial bank deposit holdings in China and more protracted transitions in household wealth, when compared to the current model.

References


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Appendix

1.A Data Construction

This appendix section details my construction of a panel dataset of housing values, prices, quantities, household purchasing power, and household wealth for Chinese cities.

I use the panel dataset to construct aggregate housing values and quantities for Chinese cities. This is necessary because data on urban housing in China is scant, even in the aggregate. Further, neither a systematic housing census for housing quantities nor measures of value of housing in flow-of-funds tables exists. I also use the panel dataset to document patterns across Chinese cities. The large number of cities in China provides useful variations in the extent of the housing boom and variations in the covariates of the housing market, which I exploit.

Some of the challenges I encountered in constructing the city panel dataset include scattered data sources, as well as measurement concepts that are sometimes not fully consistent. To make this dataset possible, I therefore make necessary simplifying assumptions.

To construct this city panel dataset, I first describe my measures for housing prices, housing values, and housing quantities. For prices, I use the housing price index in Fang et al. (2015), a constant quality housing price index constructed by comparing prices of comparable new homes in the same development that are sold
at different times. The housing price index covers 120 cities from 2003 to 2012. For housing values, I combine information from the housing price index, from the 2005 1% Mini Census microdata, and from local housing administration agencies. To do so, I follow a perpetual inventory approach:

\[ \text{Value of Urban Housing}_T = (1 - \delta)^T \cdot \frac{p_T}{p_0} \cdot \text{Value of Urban Housing}_0 \]

\[ + \sum_{t=1}^{T} (1 - \delta)^{T-t} \cdot \frac{p_T}{p_t} \cdot \text{New Urban Housing Sales}_t \]

where \( \delta \) is the depreciation rate on housing, and \( p_t \) is the housing price index in year \( t \). For the base year of 2003, I make simplifying assumptions. The 2005 1% Mini Census microdata provides building age and square footage of homes occupied at the time of the survey, from which I take only homes built in and before 2003. I compute the total square footage of homes built in or before 2003, adjusted for a depreciation rate of 1.5%, and then multiply by the average selling price per square foot of new homes in 2003, information I obtained from local housing administration agencies. I take this product to be the value of urban homes in the base year. For a non-base year, implementation of the perpetual inventory approach is straightforward. I obtain housing values in a non-base year by taking into account appreciation (through the housing price index) and depreciation, and then adding sales of new urban housing, information made from the local housing administration agencies. This particular measure includes homes that are bought in a non-base year and are left vacant; however, unbought inventory is not included in this measure.

Next, I construct a measure of household wealth for Chinese cities. The liquidity constraints mechanism predicts that the value of housing is limited by household wealth (up to some leverage). I measure household wealth at the city level by the

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17The 2005 Inter-Census Population Survey, from which I obtain a proprietary 1% random sample, conducted on 1% of the population throughout 2005.

18Therefore, this measure of housing values is closer to the concept of price times quantity demanded, rather than price times quantity supplied.
following:

\[ \text{Household Wealth} = \text{Bank Deposits} + \text{Value of Housing} - \text{Mortgage} \]

where I obtain annual city-level observations on household bank deposits and mortgage from local municipal office of finance. This measure takes into account the two largest asset classes held by Chinese urban households in terms of market size: home equity and bank deposits make up 80 to 90% of urban household wealth, according to calculations derived from two national household surveys that became available only around the end of my sample, the Chinese Household Finance Survey (CHFS) and the Chinese Family Panel Studies (CFPS). Data on holdings of other financial assets do not exist for the cities in my sample. Fortunately, non-bank financial markets are underdeveloped in China, and the majority of the household financial assets are in bank deposits. This measure also does not include the value of personal businesses. However, this omission should not matter for checking the liquidity constraint mechanism, because it is hard to borrow against (or cash out of) the value of personal businesses in China.

Finally, I also collect various measures of household purchasing power, including disposable income, retail sales, and population. Because survey-based disposable income measures in China under-samples high income persons, I overcome this data limitation by measuring disposable income as gross city output adjusted by the ratio of household disposable income in the aggregate flow-of-funds data over aggregate gross domestic output. For population, I consider both non-farm hukou population and resident population. Other proxies for the level of economic activities at the city level include electricity use (a key component of the famous Li Keqiang index) and the profits of industrial firms.
1.B Normalization of the Model

This appendix section details the procedure for normalizing the model in Section 1.4.

Given that a realization of \( g \) permanently influences \( \Gamma \), income is nonstationary with a stochastic trend. To solve the equilibrium of the model, I need to make the model variables stationary. I normalize model variables in a standard way, following Aguiar and Gopinath (2007). For any variable \( x \), I introduce a hat to denote its detrended counterpart:

\[
\hat{x}_t \equiv \frac{x_t}{\Gamma_t}
\]

with a special treatment of \( h_t, p_t, \) and \( H^S_t \) to account for the fact that the trend growth of the quantity of housing is slower than the trend growth of income:

\[
\hat{h}_t \equiv \frac{h_t}{(\Gamma_t)^{\varepsilon/(1+\varepsilon)}}, \quad \hat{H}^S_t \equiv \frac{H_t}{(\Gamma_t)^{\varepsilon/(1+\varepsilon)}}, \quad \hat{p}_t \equiv \frac{p_t}{(\Gamma_t)^{1/(1+\varepsilon)}}.
\]

In normalized form, the household maximization problem can be stated recursively:

\[
\hat{V}(\hat{w}; \hat{W}, g, z) = \max_{\{\hat{c}, \hat{a}, \hat{h}, \hat{h}\}} \left\{ E_\gamma \left( \hat{c}^{1-\theta} \hat{h}^\theta \right) \right\}
\]

\[
= \beta \left[ E \left( \left( (g')^{1-\theta/(1+\varepsilon)} \hat{V}(\hat{w}'; \hat{W}', g', z') \right)^{1-\gamma} \right) \right]^{1-\frac{1}{1-\gamma}}
\]

where

\[
\hat{c} = \begin{cases} 
\hat{c}^n & \text{with prob } 1 - \pi \\
(\hat{c}^n)^{1-\kappa} (\hat{c}^m)^{\kappa} & \text{with prob } \pi
\end{cases}
\]
subject to

$$\hat{c}^n + \hat{a} + \hat{p}(\hat{W}, g, z)\hat{h} - \hat{b} \leq z + \hat{w}, \quad (1.25)$$

$$\hat{w}' = \frac{R_a g'}{\hat{g}'}(\hat{a} - \pi \hat{c}^m - \frac{R_b g'}{g'} \hat{b} + \frac{\hat{p}(\hat{W}', g', z')}{(g')^{\epsilon/(1+\epsilon)}}(1 - \delta)\hat{h}, \quad (1.26)$$

$$0 \leq \hat{a}, \hat{b}, \quad (1.27)$$

$$\hat{b} \leq \psi(\hat{p})\hat{p}\hat{h}, \quad (1.28)$$

$$\hat{c}^m \leq \hat{a}. \quad (1.29)$$

In normalized form, (1.25) and (1.26) represent the evolution of household wealth; (1.28) and (1.29) represent the two liquidity constraints in the model: the borrowing constraint and the emergency consumption constraint, respectively. The state vector of the household maximization problem consists of individual household wealth $\hat{w}$, aggregate household wealth $\hat{W}$, trend aggregate income growth rate $g$, and transitory aggregate income state $z$.

**Recursive Equilibrium (Normalized)**

Definition: A recursive equilibrium of the model is a housing price function $\hat{p}(\hat{W}, g, z)$, a law of motion for aggregate household wealth $\hat{W}' = \hat{G}(\hat{W}, g, z, g', z')$, a value function $\hat{V}(\hat{w}; \hat{W}, g, z)$, and a collection of policy functions $\hat{c}^n(\hat{w}; \hat{W}, g, z)$, $\hat{c}^m(\hat{w}; \hat{W}, g, z)$, $\hat{a}(\hat{w}; \hat{W}, g, z)$, $\hat{b}(\hat{w}; \hat{W}, g, z)$, $\hat{h}(\hat{w}; \hat{W}, g, z)$ such that:

a. **[Optimality]**: Given the housing price function and the law of motion for aggregate household wealth, the value function and the policy functions solve the household maximization problem.

c. **[Housing market clearing]**: The housing market clears at each state:

$$\hat{h}(\hat{W}; \hat{W}, g, z) = H_0 \cdot \hat{p}(\hat{W}, g, z)^\epsilon.$$
b. [Consistency]: Given the policy functions and the housing price function, \( \hat{G} \) maps current aggregate wealth into next period aggregate wealth.

\[
\hat{G}(\hat{W}, g, z, g', z') = \frac{R_a}{g'}(\hat{a}(\hat{W}; \hat{W}, g, z) - \pi \hat{e} m(\hat{W}; \hat{W}, g, z)) - \frac{R_b}{g'} \hat{b}(\hat{W}; \hat{W}, g, z)
\]

\[
+ \frac{\hat{p}(\hat{G}(\hat{W}, g, z, g', z'), g', z')}{(g')^{\varepsilon/(1+\varepsilon)}} (1 - \delta) \hat{h}(\hat{W}; \hat{W}, g, z).
\]
Chapter 2

Heterogeneity in Consumption Responses to Long-lasting Income Shocks

2.1 Introduction

Incomplete markets models in the spirit of Aiyagari (1994), Bewley (1986) and Huggett (1993) are one of the benchmark models in macroeconomics and predict that households are not able to perfectly smooth consumption in the face of income shocks. Building on this prediction, incomplete markets models are used widely to study income inequality\(^1\) and redistribution.\(^2\) In this regard, the ability to match empirical evidence on the joint behavior of income and consumption is a key requisite if incomplete markets models are to deliver reliable predictions.

Existing results suggest that incomplete markets models do well in producing the average level of consumption responses to income shocks. In two recent stud-

\(^1\)See, for example, Storesletten et al. (2004), Heathcote et al. (2010), and Kaplan (2012a).
ies, Blundell et al. (2008) (hereafter referred to as BPP) use data from a panel of US households to estimate the degree to which households adjust consumption in the face of long-lasting income shocks, and Kaplan and Violante (2010) (hereafter KV2010) report that a calibrated life-cycle version of the incomplete markets model can rationalize the average estimate of consumption responses found in BPP.

But there are other issues for which the heterogeneity in consumption responses matters. First, proposed policies can be non-uniform in nature. For example, there is recent interest in age-dependent taxation of income and joint taxation of capital and labor, put forward by Erosa and Gervais (2002), Albanesi and Sleet (2006), Weinzierl (2011), and Farhi and Werning (2013). Second, the predictions of incomplete markets models may be important beyond the aggregate level. For example, Heathcote et al. (2010) use a calibrated incomplete markets model to show that households are affected differently by changes in the wage distribution. In both cases, the reliability of the model’s welfare implications depends on whether the model produces the correct distribution of consumption responses in the face of the proposed policies or structural changes.

Little is known, however, about the ability of incomplete markets models to predict the right distribution of consumption responses. The KV2010 model generates two sharp predictions about cross-sectional differences in consumption responses to long-lasting income shocks: the response is smaller for older households and for wealthier households. Yet BPP find no significant statistical evidence to support these predictions.\(^3\) This tension leads KV2010 to the preliminary conclusion that the model might be misaligned with the data in the cross-sections of consumption responses. The object of this paper is to revisit this tension.

\(^3\)In addition to the negative results in BPP, Etheridge (2014), using British data, also finds insignificant age differences in consumption responses. The more recent study of Arellano et al. (n.d.) make important advances in the nonlinear panel data estimation of heterogeneous consumption responses, but also do not find statistical significance at the 95% confidence level.
To do this, I use an extended PSID sample augmented with CEX expenditure information, a refined estimator, and parameter stability tests. I find statistically significant and economically important age and wealth heterogeneity in how households adjust consumption in face of long-lasting shocks to labor income. While younger households adjust log nondurable consumption by more than 50% of the size of a long-lasting shock to log after-tax labor income, households with heads older than 50 change log nondurable consumption by 25% or less of the shock size. Along the wealth dimension, households with a larger fraction of total income from liquid assets (which I interpret as a proxy for a larger liquid-wealth to labor-income ratio), are more than twice as capable of smoothing consumption over long-lasting shocks to log after-tax labor income than households with little to no income from liquid assets. My empirical results thus suggest the presence of large cross-sectional differences in the access of US households to private insurance against long-lasting income shocks. Such differences can be important for studying welfare and for designing public insurance and taxation, as discussed, for example, in Heathcote and Tsujiyama (2014).

Comparing model predictions with my empirical results, I find that incomplete markets models are in fact able to predict the correct cross-sections in consumption responses. When calibrated similarly to that of KV2010, the life-cycle incomplete markets model produces age and wealth heterogeneity in consumption responses to long-lasting income shocks that are quantitatively similar to those I find in the data. Additional features of the calibration to that of KV2010 are an empirical value of income persistence and a finer targeting of the wealth distribution. The model embeds two separate channels that allow for heterogeneous consumption responses to long-lasting income shocks. First, there is a horizon effect, in the sense that labor-income risks are truncated at retirement. Second, there is a buffer-stock effect, in the sense that households with high financial wealth relative to labor income are better buffered against income shocks of a given size. I demonstrate that the
importance of both channels is supported by the data. On the one hand, in a subsample that excludes high-wealth households, there is still a decreasing age profile of consumption responses, providing evidence for the horizon effect. On the other hand, in a subsample that excludes agents near retirement, the proxy for the liquid-wealth to labor-income ratio remains negatively correlated with consumption responses, supporting the buffer-stock effect.

The identification of consumption responses to long-lasting income shocks in this paper follows and refines the pioneering work of BPP, who construct a panel of household income and consumption from the PSID and the CEX, and document partial insurance. This study has three key differences from BPP, which fails to find significant heterogeneity in consumption responses to long-lasting shocks to labor income.4

First, I extend the PSID sample used in BPP (1980–92) to cover all years during which the PSID was carried out annually (1967–96), which nearly doubles the effective sample size. Following Guvenen and Smith (2013), I employ information from early waves of the CEX in 1972 and 1973 to impute consumption in the PSID before 1980.

Second, I use an alternative estimator, a refined version of the IV estimator proposed in KV2010. Unlike the minimum distance estimator adopted in BPP, this estimator treats year conditional variances of shocks to income as nuisance parameters. This makes the estimator more efficient in estimating consumption responses, especially in panels with a large number of years but not necessarily a large number of observations per year.

Third, to establish heterogeneity in consumption responses I apply parameter stability tests in the spirit of Andrews (1993) and Andrews and Ploberger (1994)), instead of stratifying the sample using arbitrary age/wealth cutoffs. These parameter stability tests search over a variety of break points in age and wealth and take into

4BPP does document that low-wealth households have significant consumption responses to transitory shocks to labor income, while high-wealth households do not.
account uncertainty in the estimates caused by the arbitrary nature of break points, thus preventing spurious rejection of homogeneity by using discretionary cutoffs.

This paper also expands on the empirical literature on the cross-section of consumption responses to shocks. Notable examples include Jappelli and Pistaferri (2013), who document rich heterogeneity in consumption responses to transitory government transfers, and Mian et al. (2013), who focus on wealth heterogeneity in consumption responses to shocks to household net worth.\(^5\)

In the next Section, I define the transmission coefficient of long-lasting labor income shocks to consumption—the measure of consumption responses used in this paper. In Section 2.3, I describe the data and the empirical method used in estimating age and wealth patterns in the transmission coefficient. I report my empirical results in Section 3.4. In Section 2.5, I present a calibrated life-cycle incomplete markets model and compare the heterogeneity in consumption responses in the model and in the data. Section 2.6 concludes.

### 2.2 Theory

Following BPP and KV2010, I assume that real (log) net labor income, \(\log Y\), can be decomposed into an anticipated component \(\kappa\), a persistent component \(z\), and a transitory component \(\nu\). Hence, the income process of each household \(i\) is (subscript \(t\) denotes age):

\[
\log Y_{it} = \kappa_{it} + z_{it} + \nu_{it}
\]  

\(^5\)Along the wealth dimension, the paper with findings most similar to mine is Casado (2011). He finds that households in wealthier regions of Spain have significantly lower consumption responses to long-lasting shocks to labor income than those in poorer regions. See also Carroll et al. (2014) for a review of wealth heterogeneity in the consumption response to *transitory* income shocks.
I further assume that the persistent component of labor income, $z$, follows an AR(1) process with a persistence parameter $\rho$ that is close to one:

$$z_{it} = \rho z_{it-1} + \eta_{it} \quad (2.2)$$

Here, $\eta_{it}$ denotes long-lasting shocks to labor income. The shock $\eta_{it}$ is fully permanent if $\rho$ is one; it is slowly mean-reverting if $\rho$ is less than but still close to one. The transitory component $\nu$ is an MA(1) process. This form of the income process provides a reasonably flexible but parsimonious way to capture income shocks with different persistences. Let $c_{it}$ denote log consumption of household $i$.

The transmission coefficient of long-lasting labor income shocks to consumption (hereafter the transmission coefficient), $\phi$, is defined as the covariance between changes in log consumption and long-lasting shocks to labor income, divided by the variance of such shocks:

$$\phi \equiv \frac{\text{cov}(\Delta c_{it}, \eta_{it})}{\text{var}(\eta_{it})} \quad (2.3)$$

That is, the transmission coefficient is the elasticity of consumption with respect to the persistent component of labor income. The transmission coefficient measures the degree to which consumption responds to long-lasting shocks to labor income. An alternative measure would be the marginal propensity to consume (MPC) in terms of levels. However, given that I use self-reported consumption data that do not cover all consumption categories, estimating an MPC in levels is likely to produce downward-biased results, whereas $\phi$, an elasticity-based measure, should be less susceptible to this problem. Thus, I use $\phi$ as the preferred measure of consumption responses.
2.3 Data and Empirical Method

Perhaps surprisingly, the literature contains no conclusive empirical evidence of age effects on $\phi$ and very limited empirical evidence of wealth effects on $\phi$. When BPP estimate a specification where $\phi$ is allowed to vary linearly with age, they find a negative coefficient, but it is not statistically significant (they also report a smaller $\phi$ for the cohorts born in the 1930s compared with those born in the 1940s, but the difference is again statistically insignificant). When BPP allow consumption responses to vary with wealth, they report a higher $\phi$ for the bottom quintile of the wealth-to-income ratio distribution compared with the other four quintiles but, once again, the difference is statistically insignificant.

This inconclusiveness can be attributed to two key factors. First, given their focus on the increase in income and consumption inequality over the ’80s, BPP restrict their sample to a period between 1980 and 1992, which limits their sample size. Second, while BPP’s methodology, designed to infer the year-conditional variances of permanent/transitory income shocks jointly with the transmission coefficients, is well-suited for their investigation of the composition-shift of income shocks, it also increases the degrees of freedom in the estimation and thus lowers efficiency in estimating the transmission coefficient.

I tailor BPP’s methodology to the estimation of age and wealth cross-sections of $\phi$ by making two changes in the estimation. First, I extend the income-consumption panel to the period between 1968 and 1996 to increase the sample size. Following Guvenen and Smith (2013), I exploit information in early waves of the CEX—1972 and 1973—to impute consumption in the PSID before 1980. Second, I adopt an alternative estimator, a refined version of the instrumental variable estimator described in KV2010, which improves efficiency in estimating the transmission coefficient by treating the year-conditional variances of income shocks as nuisance parameters.
I also introduce a third methodological difference by applying parameter stability tests with unknown break points, in the spirit of Andrews (1993) and Andrews and Ploberger (1994). This type of parameter stability test searches over various break points in age and wealth, but also takes into account uncertainty in the estimates resulting from the arbitrary nature of the break points. Such tests do not necessarily make it easier to reject homogeneity in $\phi$, compared with using arbitrary cutoffs in age and/or wealth, but they allow me to test for heterogeneity in consumption responses more thoroughly. These tests are explained in detail in Section 4.

2.3.1 Description of Data: Extending BPP’s Sample

Estimating the transmission coefficient $\phi$ in the age and wealth cross-sections requires a panel with measures of income, consumption, age and wealth. I use data from the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Interview Survey (CEX), both from the United States.

The PSID is a panel of US households with detailed and continuously available information on demographics and income. I focus on the years during which the PSID is carried out annually, which results in data that cover age and net labor income for the period 1968–96. I use the age of the head of the household as the measure for age. The PSID reports total family income and its components: wages and salaries, transfer income, and asset income. I compute net labor income by adding wages and salaries to transfer income, and subtracting imputed federal income tax on non-asset income.\(^6\) I use the measure of asset income in the PSID as a proxy for wealth. A detailed measure of asset income is regularly available since 1974, which includes interest, dividends, rent on non-owner-occupied housing, and the asset portion of income from unincorporated businesses/farms, but excludes service flows.

\(^6\)I impute federal income tax on non-asset income using TAXSIM for the years 1977–96, and I assume that couples file jointly. For years prior to 1977, when TAXSIM is not applicable, I use the imputed federal income tax variable provided in the PSID.
from owner-occupied housing.\textsuperscript{7} It is reasonable to assume that households with higher asset income also have a higher level of wealth. Accordingly, I use the ratio of asset income to labor income as a proxy for the liquid-wealth-to-income ratio. I recognize that this could be a noisy measure, but it is the best measure regularly available in the PSID during the sample period.\textsuperscript{8}

Consumption measures in the PSID are limited to food expenditures (available annually for 1968–96 except in 1972, 1987 and 1988) and occasionally some other items such as utilities. The CEX, on the other hand, has detailed information on household expenditures, but lacks the panel dimension of the PSID. I create imputed panel measures of nondurable consumption by combining the information in both the PSID and the CEX. Following BPP, I estimate a demand system in the CEX, in which log food expenditures (food at home and food in restaurants) is a linear function of log nondurable expenditures,\textsuperscript{9} demographics and calendar time. I then invert the estimated demand system for food to map food expenditures, demographics and calendar time in the PSID into imputed nondurable expenditure. BPP use information in only the continuous CEX, starting in 1980. I follow Guvenen and Smith (2013) and include information in the early wave of the CEX, 1972 and 1973, to impute nondurable expenditure in the PSID prior to 1980. I also incorporate recent suggestions in Campos and Reggio (2014) that improve on the original choice of instrumental variables in BPP to avoid bias in the estimated demand system. Table 2.B reports detailed demand system estimates used in the imputation of nondurable expenditure in the PSID sample.

\textsuperscript{7}Values of owner-occupied housing are reported separately, but the value of housing equity is not typically available. Moreover, owner-occupied housing is not a very liquid form of wealth.

\textsuperscript{8}Wealth supplements offered in survey years 1984, 1989 and 1994 offer potentially better wealth measures, but since I need contemporaneous values the resulting sample size would be prohibitively small.

\textsuperscript{9}I use the same definition of nondurable expenditure as Attanasio and Weber (1995) and BPP, which includes food, alcohol, tobacco, and expenditures on other nondurable goods, such as services, heating fuel, public and private transport (including gasoline), personal care, and semidurables (defined as clothing and footwear), and excludes expenditures on health and education, which are more durable and more dependent on family composition.
My sample selection procedure is standard. I restrict the focus to households in the PSID Core sample, headed by a male, aged 25 to 65, and not reported to be retired. I drop households with missing information on race, education, or state of residence, and I drop income growth outliers,\(^ {10}\) or those who have top-coded income, food expenditure or taxes. Conditional on these criteria, I consider both a sample of continuously married couples and an unrestricted sample of households.

Extending the sample from 1968 to 1996 (relative to 1980–92) nearly doubles the effective sample size available for estimation.\(^ {11}\) This paper’s estimator (described below) requires observing income in the past three, the current and the next two years, and consumption in the current and the past year. For statistical power, I want a large sample size. With BPP’s age restriction of 30 to 65, their sample would yield 5120 valid observations, while the extended sample yields 9887. With my age restriction of 25 to 65, BPP’s sample would yield 6464 valid observations, while the extended sample yields 12273. This increase in sample size is crucial, given that I want to estimate heterogeneity in \(\phi\) in the cross-section.

### 2.3.2 Estimating the Transmission Coefficient

I broadly follow the instrumental variable procedure described in KV2010 to estimate the transmission coefficient of long-lasting income shocks to consumption (\(\phi\)). The

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\(^{10}\) Defined as those whose income grows more than 500%, falls by more than 80%, or with an income level below $100.

\(^{11}\) The years between 1993 and 1996 warrant some comments. Prior to 1993, an annualized measure of food expenditure is available from the PSID, whereas since 1993 food expenditure is recorded in disaggregated time periods, so that no official annualized measure is available, and the user is responsible for time aggregation. I check the quality of my time-aggregation procedure by exploiting the fact that both the time-disaggregated measure and the official annualized measure are available for 1992. I confirm that my annualized measure matches the official annualized measures provided by the PSID almost perfectly. As a side note, BPP do not use data between 1993 and 1996 in their main estimation, but they do consider these years in an unpublished sensitivity analysis that they report to maintain their overall results.

I also note that the variance of transitory changes in reported food expenditure in the PSID is larger during 1993–96 than before 1993, indicating a larger measurement error in consumption, possibly due to the switch to a computer-assisted interview system. As will become clear later, I ensure that the estimate of consumption responses to long-lasting income shocks used in this paper is robust to classical measurement error in consumption.
estimator assumes unit persistence of long-lasting shocks to income, but performs reasonably well when misspecified (for $\rho$ close to 1), as shown in the Appendix. Other identifying assumptions are: (1) income shocks are serially uncorrelated, (2) log consumption changes are orthogonal to non-contemporaneous shocks to log-income, and (3) transitory income shocks are MA(1).\(^{12}\)

To identify $\phi$, define $g^c_{it}(y_i) \equiv \Delta y_{it} + \Delta y_{i,t+1} + \Delta y_{i,t+2}$ and $g^y_{it}(y_i) \equiv \Delta y_{i,t-2} + \Delta y_{i,t-1} + \Delta y_{i,t+1} + \Delta y_{i,t+2}$. It follows that

$$
\phi \equiv \frac{\text{cov}(\Delta c_{it}, \eta_{it})}{\text{var}(\eta_{it})} = \frac{\text{cov}(\Delta c_{it}, g^c_{it}(y_i))}{\text{cov}(\Delta y_{it}, g^y_{it}(y_i))}.
$$

Identification in the data is achieved by substituting sample covariances in (2.4). Standard errors are obtained by a bootstrap with 250 repetitions, clustering over households.\(^{13}\)

Intuitively, the estimator captures the degree of comovement between consumption and income shocks that last through at least three years. To compare with the original IV estimator in KV2010, note that if $g^c_{it}(y_i)$ is the same as $g^y_{it}(y_i)$, the estimator is precisely that described in KV2010; the covariance between $\Delta c_{it}$ and $\eta_{it}$, however, is better estimated using the sample covariance between $\Delta c_{it}$ and $g^c_{it}(y_i)$ rather than using the sample covariance between $\Delta c_{it}$ and $g^y_{it}(y_i)$.

The difference between $g^c_{it}(y_i)$ and $g^y_{it}(y_i)$ represents a small refinement to the IV estimator in KV2010. The major difference between my estimation (or any other estimation of $\phi$ akin to the IV estimation in KV2010) and BPP’s minimum distance estimation, however, lies in the fact that I treat the year-conditional variances of $\eta_{it}$ as nuisance parameters (which need not be explicitly estimated along with $\phi$), whereas in

\(^{12}\)I use the same identification assumptions as BPP. The third assumption is motivated by the fact that log income growth is significantly negatively correlated at the first and the second lag in my sample; the same pattern that prompts BPP to assume an MA(1) transitory income component.

\(^{13}\)In this particular case, clustered standard errors are preferable and often smaller than non-clustered ones because there is negative intra-cluster correlation in independent variables. Most of the results remain unchanged, however, when using non-clustered standard errors.
BPP’s minimum distance estimation the year-conditional variances of $\eta_{it}$ are always explicitly estimated.\(^{14}\) In panels with relatively large $T$ and relatively small $N$, BPP’s minimum distance estimation does not benefit as much from the increase in $T$, since degrees of freedom also increase with $T$, whereas estimations analogous to the IV in KV2010 take full advantage of increases in the length of the sample in the estimation of $\phi$.\(^{15}\)

Given that I focus exclusively on estimating $\phi$, the estimator based on (2.4) is a natural choice over BPP’s original minimum distance procedure. I report a Monte Carlo exercise in the Appendix which further shows that the estimator used in this paper is robust to measurement errors in income and consumption and performs reasonably well when misspecified (for $\rho$ close to 1).

When implementing the estimator, I use the measures of nondurable expenditure and net labor income described in Section 2.3.1. I control for the anticipated component in log net labor income by removing age effects and year effects, interacted with level of education. I also control for potential year-specific imputation bias in log nondurable expenditure (log consumption) by removing year effects. The residual log income and log consumption are then used in the estimation of $\phi$.\(^{16}\)

\(^{14}\)The year-conditional variances of $\eta_{it}$ are allowed to vary under both methods.

\(^{15}\)I note that the property of BPP’s minimum distance procedure is not well understood under small $N$, which warrants further investigation in its own right. I encounter convergence problems in several cases when I use BPP’s minimum distance procedure to estimate $\phi$ for high/low age groups, using different age thresholds in their 1980–92 sample.

\(^{16}\)I follow the semiparametric approach in Fernandez-Villaverde and Krueger (2007) and simultaneously estimate year effects using year dummies and age effects as a smooth function of age (non-Caucasian observations—around 5% of the sample—have to be dropped in this step due to lack of information in estimating education-specific age effects). Any fixed effects in income or consumption, for example cohort effects, would be controlled for when I take the first difference in income and consumption. I experiment with various controls that might lead to anticipated or spurious changes in income and/or consumption (such as family composition), and I also experiment with different specifications of age effects in income/consumption. The heterogeneity results that I report are scarcely affected by changes along these dimensions.
2.4 Empirical Results

Before looking at the age and wealth cross-sections of $\phi$, I first confirm that my sample and estimation method produce a reasonable average estimate of $\phi$ relative to existing results in the literature. When I do not restrict family type in the sample, the average estimate of $\phi$ is 0.47, with a standard error of 0.05. When I look at only continuously married couples, the average estimate of $\phi$ is 0.37, with a standard error of 0.07. While my average estimate of $\phi$ might seem low, it is actually similar to results reported in other studies. For example, Etheridge (2014) finds an average $\phi$ of 0.42 using British data, with a standard error of 0.14. Although BPP’s preferred number for $\phi$ is 0.64, they remove the effects of employment changes from the stochastic components of income and consumption. If the effects of employment changes on income and consumption were not removed, as here and in Etheridge (2014), their estimate of $\phi$ would be 0.43, with a standard error of 0.06.

The transmission coefficient seems to be constant over the sample period: in both cases, I cannot reject a constant $\phi$ before and after 1980 or in 1985 (the target year of a time-break test in BPP). In what follows, I restrict the transmission coefficient as constant over the whole period.

2.4.1 Age Profile of Consumption Responses in the PSID

Figure 2.1 displays rolling estimates of $\phi$ by age. Specifically, the rolling estimate of $\phi$ at each age $i$ is the estimate of $\phi$ in a subsample with ages between $i-2$ and $i+2$, including endpoints. Confidence intervals at the 95% level are plotted as well.

Two observations arise from Figure 2.1. First, there is some evidence that $\phi$ is lower for households with heads older than 51. In the unrestricted sample, rolling estimates of $\phi$ for those aged above 51 are low (below 0.3) and not statistically

---

17 This is also the approach taken in Hall and Mishkin (1982). Given that employment changes are largely unanticipated, it is natural to include the effect of employment changes when constructing the stochastic components.
distinguishable from zero, whereas for those aged below 49 the rolling estimates of $\phi$ are high (between 0.4 and 0.8) and statistically different from zero. The evidence is weaker in the continuously married sample, as rolling estimates of $\phi$ are lower for those above 51 as well as for those in their mid-30s. Second, the standard errors for the rolling estimates are large, ruling out conclusions of an age effect.  

Table 2.1 provides another way to examine the age pattern in consumption responses to long-lasting income shocks. When the sample is grouped by age bins, there is again some evidence of a decreasing pattern with age, although standard errors are large.

Given that large standard errors preclude statistical conclusions when estimating $\phi$ for narrower age groups, a logical next step is to combine age groups to reduce standard errors. The data allow me to follow Chow (1960), Andrews (1993), and Andrews and Ploberger (1994) and perform parameter stability tests of $\phi$ over age, assuming either known break points in the case of Chow (1960) or unknown break points in the case of Andrews (1993) and Andrews and Ploberger (1994). Although

\footnote{A similar figure that plots rolling estimates in the original BPP sample with continuously married couples aged from 30 to 65 is available upon request. There, the point estimates share similar features with the right-hand panel of Figure 2.1. Standard errors are even larger, as expected with a smaller sample size.}
Table 2.1: Transmission Coefficient for Age Bins

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Unrestricted</th>
<th>Married</th>
</tr>
</thead>
<tbody>
<tr>
<td>$28 \leq \text{age} &lt; 30$</td>
<td>0.41 0.14</td>
<td>0.65 0.21</td>
</tr>
<tr>
<td>$30 \leq \text{age} &lt; 35$</td>
<td>0.50 0.13</td>
<td>0.38 0.15</td>
</tr>
<tr>
<td>$35 \leq \text{age} &lt; 40$</td>
<td>0.67 0.15</td>
<td>0.32 0.20</td>
</tr>
<tr>
<td>$40 \leq \text{age} &lt; 45$</td>
<td>0.63 0.14</td>
<td>0.66 0.19</td>
</tr>
<tr>
<td>$45 \leq \text{age} &lt; 50$</td>
<td>0.76 0.26</td>
<td>0.51 0.31</td>
</tr>
<tr>
<td>$50 \leq \text{age} &lt; 55$</td>
<td>0.04 0.26</td>
<td>0.14 0.21</td>
</tr>
<tr>
<td>$55 \leq \text{age} &lt; 60$</td>
<td>0.21 0.12</td>
<td>0.11 0.11</td>
</tr>
<tr>
<td>$60 \leq \text{age} \leq 62$</td>
<td>0.15 0.19</td>
<td>0.20 0.23</td>
</tr>
</tbody>
</table>

Figure 2.2: Chow Tests of Consumption Responses (at Various Age Thresholds)

the parameter break tests in Andrews (1993) and Andrews and Ploberger (1994) are designed for a one-time change in the parameter, they are shown to have power against more general forms of parameter instability and can therefore be applied to cross-sectional heterogeneity in $\phi$. I start with the simple case of known break points; i.e., the Chow test. For different ages, I estimate $\phi$ separately for the sample with household heads strictly older than the threshold and the sample with household heads weakly younger than the threshold, and test for equality in $\phi$. 

75
Figure 2.2 displays the results from this exercise. The horizontal axis displays different age thresholds (“potential breaks”). Each point marked by a solid circle is the estimated transmission coefficient for households with heads whose ages fall below the corresponding age threshold ($\hat{\phi}_L$). Each point marked by a cross is the estimated transmission coefficient for households with heads whose ages are greater than or equal to the corresponding age threshold ($\hat{\phi}_G$). The bands around each pair of circles and crosses illustrate a Chow test; i.e., a two-sided test of age homogeneity in consumption responses with a known break point ($H_0 : \phi_L = \phi_G$), with width of the bands set to $k\sqrt{(\hat{se}_G)^2 + (\hat{se}_L)^2}$, where $1 - \Phi(k) = 0.025$ and $\Phi(\cdot)$ denotes the cdf of a standard normal distribution.

Figure 2.2 is designed so that the null hypothesis, $H_0$, of the Chow test is rejected at a certain age threshold if, and only if, the two bands do not overlap. Notice that for age thresholds 45 to 58, the null hypothesis is rejected (in both the unrestricted sample and the continuously married sample): the consumption response of households with heads aged 45 or older (or 46, ..., or 58) is significantly smaller than that of households with heads younger than 45 (or 46, ..., or 58).\(^{19}\)

Differences in the point estimates between the younger groups and the older groups are large, further highlighting the economic significance. Taking the midpoint age threshold of 45 as an example, the average $\phi$ of the younger group is 0.59 in the unrestricted sample (0.52 in the continuously married sample), while the average $\phi$ of the older group is 0.25 (0.16 in the continuously married sample), a difference of 0.34 (0.36 in the continuously married sample).

To ensure that the age-heterogeneity results are robust to alternative choices of the age break, I apply a class of parameter stability tests with unknown break points, described in Andrews (1993) and Andrews and Ploberger (1994). In essence, if the

---

\(^{19}\)A similar figure is available upon request for the same exercise applied to the original BPP 1980–92 sample. I cannot establish age heterogeneity, partly because of large standard errors.
Chow test for each known age break is:

\[ F(\text{age}) = \frac{\left(\hat{\phi}_L - \hat{\phi}_G\right)^2}{(s\hat{\text{e}}_G)^2 + (s\hat{\text{e}}_L)^2} \]  

(2.5)

then under the null hypothesis that \( H_0 : \hat{\phi}_L^n(\text{age}) = \hat{\phi}_G^n(\text{age}), \forall \text{age} \in [a, \bar{a}] \), I can find the distribution for the following tests and reject the null hypothesis of age homogeneity in \( \phi \) if the sample value of \( \text{SupF} \) (\( \text{ExpF} \), \( \text{AveF} \)) is higher than a critical value:

\[
\text{SupF} = \sup_{a_1 \leq \text{age} \leq a_2} F(\text{age}) \quad (2.6)
\]

\[
\text{ExpF} = \ln \left( \frac{1}{a_2 - a_1 + 1} \sum_{\text{age} = a_1}^{a_2} \exp \left( \frac{1}{2} F(\text{age}) \right) \right) \quad (2.7)
\]

\[
\text{AveF} = \frac{1}{a_2 - a_1 + 1} \sum_{\text{age} = a_1}^{a_2} F(\text{age}) \quad (2.8)
\]

The tests take into account the uncertainty in the estimated transmission coefficients for the younger group and the older group due to arbitrariness in the age thresholds. Applying these tests to the sample, I confirm that the earlier conclusion holds: In both the unrestricted sample and the continuously married sample, the \( \text{ExpF} \) and \( \text{AveF} \) tests reject age homogeneity at the 5% significance level. The \( \text{SupF} \) test rejects age homogeneity at the 5% significance level in the unrestricted sample, and at the 10% significance level in the continuously married sample.\(^20\)

In summary, when applying parameter stability tests, I find that there is both statistically significant and economically significant age heterogeneity in consumption responses to long-lasting income shocks (or equivalently, age difference in \( \phi \)). This

\(^20\)Following Andrews (1993), I set \( a_1 \) and \( a_2 \) to exclude the highest and lowest 15% of the age thresholds when calculating the test statistics. I use Monte Carlo methods to compute the critical value of the tests: I simulate the value of \( \text{SupF}, \text{ExpF}, \text{AveF} \) under the null hypothesis (with \( \phi \) set at the average estimate), the income process (1) and a log-linear consumption rule many times, and find approximate distributions of the test statistics. The approximate test statistic distribution that I obtain turns out to be insensitive to the parameterizations used in the simulations.
Table 2.2: Age Heterogeneity in Consumption Responses: Linear Specification

\[ \phi(\text{age}_{it}) = \phi_0 + \phi_1 (\text{age}_{it} - \text{ave}(\text{age}_{it})) \]

<table>
<thead>
<tr>
<th></th>
<th>Unrestricted</th>
<th></th>
<th>Continuously-Married</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>point estimate</td>
<td>standard error</td>
<td>point estimate</td>
<td>standard error</td>
</tr>
<tr>
<td>( \phi_0 )</td>
<td>0.487***</td>
<td>0.068</td>
<td>0.406***</td>
<td>0.079</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>-0.012**</td>
<td>0.006</td>
<td>-0.015**</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Conclusion holds independently of whether I assume that the econometrician knows the exact age points at which \( \phi \) changes.

I also consider a parametric approach of the sort used in BPP. When I allow for a linear effect in age in the estimation of \( \phi \), I obtain a significant negative coefficient, as reported in Table 2.2. The parametric estimates imply a drop of .31 in \( \phi \) from .61 at age 30 to .31 at age 55 in the unrestricted sample, and a corresponding drop of .37 in \( \phi \) (from .57 at age 30 to .20 at age 55) in the continuously married sample.

### 2.4.2 Wealth Heterogeneity in Consumption Responses

Next, I consider the effect of wealth on \( \phi \). I first report empirical estimates of \( \phi \) for different wealth groups. I sort households by their position in the year-specific, asset-income-to-labor-income ratio (AY/LY) distribution. I then ask whether a household’s wealth (as measured by AY/LY) in the past year influences its ability to insure against long-lasting income shocks in the current year. Table 2.3 shows that quintiles higher up in the AY/LY distribution do have lower point estimates of \( \phi \). The point estimates suggest that households in the highest quintile of the AY/LY distribution are more than twice as capable of smoothing consumption over long-lasting labor income shocks than households in the lowest two quintiles, who have little to no income from liquid assets.

Figure 2.3 summarizes the results from a parameter stability test in \( \phi \) over wealth, conducted in the same way as that in Section 4.2, with deciles in the year-specific
Table 2.3: Transmission Coefficient for Quintiles in the AY/LY Ratio Distribution

<table>
<thead>
<tr>
<th>AY/LY Group</th>
<th>Unrestricted</th>
<th>Married</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{\phi}$</td>
<td>median(AY/LY)</td>
</tr>
<tr>
<td>bottom quintile</td>
<td>0.71</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(.11)</td>
<td>(.12)</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>0.71</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.11)</td>
</tr>
<tr>
<td>3rd quintile</td>
<td>0.70</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(.12)</td>
<td>(.14)</td>
</tr>
<tr>
<td>4th quintile</td>
<td>0.43</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(.13)</td>
<td>(.15)</td>
</tr>
<tr>
<td>top quintile</td>
<td>0.31</td>
<td>0.250</td>
</tr>
<tr>
<td></td>
<td>(.11)</td>
<td>(.12)</td>
</tr>
</tbody>
</table>

AY/LY ratio distribution as potential cut-offs. The parameter stability tests (assuming either known or unknown break points) all reject the null hypothesis of wealth homogeneity in $\phi$ at the 5% significance level. The test and the point estimates suggest that higher wealth does reduce the consumption response to long-lasting income shocks, and that the effect of wealth on $\phi$ is both statistically and economically significant.

The results for wealth are not without issues. First, unlike age, which is nearly perfectly measured, the wealth/labor-income ratio in the current results is proxied by the asset-income/labor-income ratio. Second, asset income in the PSID includes income from business, farm and rents. I examine what portion of the wealth results is driven by business-owners, farm-owners, or second-home (for rental) owners, who might be systematically different from workers. When I remove these groups, which

---

21 I examined the quality of this proxy using the direct wealth measures in the PSID (available in survey years 1984, 1989, 1994 and biennially after survey year 1999) and found little correlation. It is unclear whether this is due to the quality of the PSID direct wealth measures (which are imputed using answers to bracketed questions), or due to the nature of the proxy.
make up less than 10% of the sample, and consider only interest/dividend/trust income relative to labor income, it is reassuring that I still find differences in the point estimates for $\phi$ across quintiles of the AY/LY ratio distribution, but the differences are now smaller and not statistically significant.

Notwithstanding these drawbacks, the results do confirm a wealth effect on consumption insurance against long-lasting labor-income shocks. The cautionary notes call for further work to refine the estimation of this wealth effect.

2.4.3 Discussion

Because age is correlated with wealth in the data, it is of interest to ask whether there is an age effect independent of wealth, and vice versa. Intuitively, age exerts an independent force, since shocks late in life are effectively less permanent. I try to separately identify the conditional effects of age and wealth with the following two exercises.
For the conditional effect of age on $\phi$, I re-estimate the age profile of consumption responses, excluding high-wealth households. When I exclude households in the highest quintile of the AY/LY distribution, the age-heterogeneity results are almost unchanged: while the standard errors become somewhat larger, parameter stability tests reject age homogeneity in $\phi$ at the 5% significance level. This suggests that the conditional effect of age does contribute in generating the empirical decreasing age profile of $\phi$. As a stricter test, I also experiment with excluding households in both the highest and the second-highest quintiles in the AY/LY distribution when re-estimating the age profile of consumption responses. Not surprisingly, a further increase in the standard errors precludes statistical conclusions in this stricter test, but the point estimates still display patterns similar to those found in Section 2.4.1.

For the conditional effect of wealth on $\phi$, I re-estimate the effect of wealth on consumption responses excluding households with heads older than 55 (or, as a stricter test, excluding households with heads older than 50). Table 2.4 displays the results. In both the unrestricted and the continuously married samples, the results suggest similar heterogeneity across wealth quintiles when households with older heads are excluded. Parameter stability tests reject wealth homogeneity in $\phi$ at the 10% significance level in all cases, and reject wealth homogeneity in $\phi$ at the 5% significance level if I exclude only households with heads older than 55. This provides evidence that the conditional effect of wealth is also at play in generating heterogeneity in $\phi$.

2.5 Accounting for Heterogeneity in $\phi$

As noted in the introduction, life-cycle versions of incomplete markets models predict that consumption responses to persistent income shocks decrease with both age and wealth. Having presented empirical evidence in support of these qualitative predic-
tions, in this section I examine whether these estimated responses are quantitatively consistent with a reasonably calibrated version of this model.

2.5.1 The Model and the Calibration

The model and its calibration follow KV2010, except that: 1) I use the empirically estimated persistence of the income process; and 2) I estimate relative risk-aversion, the discount factor, and looseness of the borrowing limit jointly, using wealth moments.

The economy consists of a continuum of households with time-separable CRRA preferences over consumption; there are no bequest motives. There is no aggregate uncertainty. Until retiring at $T_{\text{ret}}$, each household receives net labor income $Y_{it}$ governed by the process characterized in equations (2.1) and (2.2). After $T_{\text{ret}}$, households receive social security transfers as a function $P(\cdot)$ of the average of gross pre-retirement labor income $\bar{Y}_i = \frac{1}{T_{\text{ret}}} \sum_{t=1}^{T_{\text{ret}}} \bar{Y}_{it}$.\footnote{A tax function $\tau_{it} = \tau(\bar{Y}_{it})$ implies a one-to-one mapping between net labor income and gross labor income at each age ($\tilde{Y}_{it} = \bar{Y}_{it} - \tau(\bar{Y}_{it})$).} At each age $t > T_{\text{ret}}$, households survive with probability $\xi_t$. At a final age $T$, households terminate with certainty. Households trade one-period bonds at a fixed interest rate $R$ (taken as given), with

<table>
<thead>
<tr>
<th>Group</th>
<th>Unrestricted</th>
<th>Married</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All $\leq 55$</td>
<td>$\leq 50$</td>
</tr>
<tr>
<td></td>
<td>$\phi$</td>
<td>$\phi$</td>
</tr>
<tr>
<td>bottom quintile</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>3rd quintile</td>
<td>0.70</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>4th quintile</td>
<td>0.43</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>top quintile</td>
<td>0.31</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.13)</td>
</tr>
</tbody>
</table>
a borrowing limit $A_{it} \geq \underline{A}_{it}$, defined as:

$$
\underline{A}_{it+1} \equiv \sum_{\tau=t+1}^{T_{ret}} \left( \frac{\psi}{R} \right)^{\tau} \min(Y_{it}) + \left( \frac{\psi}{R} \right)^{T_{ret}-t} \sum_{\tau=T_{ret}+1}^{T} \left( \frac{1}{R} \right)^{\tau} P(\min(\tilde{Y}_i))
$$

This form follows Guvenen and Smith (2013), where $\psi \in [0, 1]$ measures the looseness of the borrowing limit. Lowest future income realizations are discounted at rate $R/\psi$ until $T_{ret}$ and at rate $R$ afterwards. The natural borrowing limit corresponds to $\psi = 1$. The zero borrowing limit effectively corresponds to $\psi = 0$. Intermediate cases of the borrowing limit are captured by $\psi \in (0, 1)$. Initial conditions $A_{i0}, z_{i0}$ are drawn from a joint distribution $H(A_{i0}, z_{i0})$. Households have access to a perfect annuity market, which allows me to formulate household $i$’s problem:

$$
V(A_{i0}, z_{i0}, \varepsilon_{i0}) = \max_{(C_{it}, A_{it})} \sum_{t=0}^{T} \beta^t C_{it}^{1-\gamma} \frac{1}{1-\gamma}
$$

subject to:

$$
C_{it} + A_{it+1} \leq RA_{it} + Y_{it}, \quad A_{it+1} \geq \underline{A}_{it+1} \quad \text{for } t \leq T_{ret}
$$

and

$$
C_{it} + A_{it+1} \leq RA_{it} + P(\tilde{Y}_i), \quad A_{it+1} \geq \underline{A}_{it+1} \quad \text{for } t > T_{ret}
$$

where $Y_{it}$ follows (2.1), (2.2).

The model is calibrated as follows. Each household enters the model at age 25 and retires at age 65.\textsuperscript{23} Terminal age is 90. The interest rate is taken to be exogenous and set to 3\%. The mapping between gross and net labor income follows Gouveia and Strauss (1994). The social security transfer function $P(\cdot)$ mimics the actual system in 1990; benefits are a piecewise linear function of average gross labor income during

\textsuperscript{23}This is a departure from KV2010, which uses 60 as the retirement age. I use 65 to be consistent with the estimates in Section 3.4.
working life. The initial conditions for income and wealth are chosen to match data from the PSID and the Survey of Consumer Finances (SCF). The income profile is estimated from the PSID. Variance of the long-lasting income shocks is taken to be age-invariant and chosen to match the empirical life-cycle increase in income mean and dispersion. Following the method in Guvenen (2009), I estimate the persistence parameter $\rho$ for the income process to be 0.964 in my sample. I choose the rest of the parameters to match key features of the wealth distribution. I first estimate the distribution of the working-life wealth-to-income ratio in the SCF from 1983 to 1995, excluding the top 5% in wealth, given that the PSID undersamples the top of the wealth distribution. I then take three parameters $\beta$, $\gamma$ and $\psi$ as free parameters, and estimate the model using six moments from the SCF: the fraction of households with negative net worth, and the 10th, 25th, 50th, 75th and 90th percentile of the working-life wealth-to-income distribution. I estimate a discount factor $\beta$ of 0.93, a relative risk aversion $\gamma$ of 3.03, and a looseness parameter of the borrowing limit $\psi$ of 0.26.

Table 2.5 lists both the data and the model moments for the wealth-to-income ratio distribution. The results suggest that the model fits the target distribution of the working-life, wealth-to-income ratio well.

---

24I measure wealth in the SCF as net worth and income as gross labor income. To conform with sample selection in the PSID, I exclude households in the SCF with heads younger than 25 or older than 65, or households with female heads. To ensure that the wealth-to-income ratio is not biased upward due to low income observations, I look at households with at least one member working full-time and making an annual labor income no lower than the minimum hourly wage times 2000 annual hours.
Figure 2.4: Age Profile of Consumption Responses in the Data and in the Model

2.5.2 Model Results

Figure 2.4 plots the age profile of transmission coefficients in the model against the age profile of transmission coefficients in the data. I simulate an artificial panel of 50,000 households to calculate the model’s transmission coefficients.

The calibrated model predicts an age profile of consumption responses that is quantitatively similar to that found in the data. Consumption responses to long-lasting shocks to labor income decrease with age in the calibrated model. The left-hand panel of Figure 2.4 shows that the model-generated age profile of $\phi$ is within the 95% confidence interval at most age points for the unrestricted sample. In terms of the point estimates, the model accounts for around 75% of the drop in $\phi$ from age 40 to retirement. The model overpredicts $\phi$ for those younger than 32, which is due mainly to the fact that $\psi$ is estimated to be low, leading to a tight borrowing limit. The literature offers two solutions to this problem. First, the young might have access to insurance within the extended family through non-monetary channels. For example, Kaplan (2012b) shows that the option of moving back with parents is quantitatively relevant in providing insurance for young workers. Second, the persistence of income shocks might be lower for young workers, as shown in Karahan and Ozkan (2013).
The right-hand panel of Figure 2.4 compares model predictions with estimates from the continuously married sample. The model matches the age decline in $\phi$ in the continuously married sample, but overpredicts the average consumption response.\footnote{The model average $\phi$ is 0.57. The empirical average $\phi$, as reported in Section 4, is 0.47 (standard error 0.05) in the unrestricted sample, and 0.37 (standard error 0.07) in the continuously married sample.} The fit for ages around 35 is somewhat worse for this sample.

To ensure conformity in comparison with the empirical results, the model’s transmission coefficients above and in what follows are calculated using the same IV estimator as in Sections 3 and 4. A close alternative would be to calculate the model’s transmission coefficients directly from the realizations of the individual shocks. This is feasible in the model and produces the true value of $\phi$, but is not feasible for the actual data. In the model, the value of $\phi$ calculated by the IV estimator is close to the true value but can contain an upward bias, the size of which depends on the fraction of constrained households, as pointed out by KV2010.\footnote{The origin of the bias is as follows: In the model, borrowing-constrained households who receive transitory negative income shocks will expect consumption to increase in the near future. This creates a negative correlation between consumption growth and lagged transitory income shocks, which violates one of the orthogonality conditions of the IV estimator.} However, in Figure 2.7 of the Appendix, I show that this upward bias is quantitatively small when the model’s age profile of $\phi$ is calculated. This is because the fraction of constrained households is small at each age in the calibrated model.

From Table 2.6 it can be seen that the model also produces wealth effects on consumption responses that are similar to those found in the data. Given that the ratio of asset income to labor income in the model is just a scaled version of the wealth-to-labor-income ratio (the interest rate is age invariant), I sort observations in the simulated data and in the PSID data by the ratio of asset income to labor income. The values of $\phi$ in the model decrease with wealth within the confidence intervals of the empirical estimates in all but the bottom wealth quintile. Moreover, the bias of the IV in the model is also small in those quintiles. The bottom wealth quintile has a
Table 2.6: Wealth Difference in $\phi$, in the Data and in the Model

<table>
<thead>
<tr>
<th>Group</th>
<th>Unrestricted</th>
<th>Married</th>
<th>Model (IV)</th>
<th>Model (True)</th>
</tr>
</thead>
<tbody>
<tr>
<td>bottom quintile</td>
<td>0.71(0.11)</td>
<td>0.60(0.12)</td>
<td>0.86</td>
<td>0.78</td>
</tr>
<tr>
<td>2nd quintile</td>
<td>0.71(0.10)</td>
<td>0.61(0.11)</td>
<td>0.65</td>
<td>0.67</td>
</tr>
<tr>
<td>3rd quintile</td>
<td>0.70(0.12)</td>
<td>0.42(0.14)</td>
<td>0.57</td>
<td>0.58</td>
</tr>
<tr>
<td>4th quintile</td>
<td>0.43(0.13)</td>
<td>0.37(0.15)</td>
<td>0.45</td>
<td>0.47</td>
</tr>
<tr>
<td>top quintile</td>
<td>0.31(0.11)</td>
<td>0.14(0.12)</td>
<td>0.34</td>
<td>0.33</td>
</tr>
</tbody>
</table>

high model transmission coefficient. But that is partly caused by the upward bias of the IV estimator associated with a large number of constrained households; the true model transmission coefficient in the bottom wealth quintile is 0.78. Therefore, one potential resolution of the discrepancy in $\phi$ between the model and the data in the bottom wealth quintile, is that households in the bottom wealth quintile of the data are, in fact, not as constrained as those in the calibrated model, such that the the IV bias is present in the model but not in the data.\(^{27}\) In that case, one should compare empirical values in the bottom quintile with the true model transmission coefficient, which would suggest a reasonable fit.

In the model, two forces drive the age and wealth heterogeneity in consumption responses. First, there is a horizon effect. As agents get closer to the end of their working lives, any given persistent income shock has less time to play out, reducing its impact on consumption. Corresponding to the earlier discussion in Section 2.4.3, this is the conditional effect of age in the model. Second, there is a buffer-stock effect. As households accumulate more financial wealth relative to their labor income, they can better insure against income shocks. This is the conditional effect of wealth in the model.

Figure 2.5 displays the conditional effects of age and wealth on $\phi$ in the model. Household-age observations in the simulated data are first sorted by the position in

\(^{27}\)The idea that some households in the data might be less constrained than those in the pure self-insurance model is consistent with the findings in Heathcote et al. (2009) and KV2010.
quintiles of the overall working-life distribution of the wealth-to-income ratio. For each quintile of the wealth-to-income ratio distribution, I then plot $\phi$ at each age where there are more than 50 observations. To reveal what really occurs in the model, the true values of $\phi$ are plotted. Thus, the results illustrated in Figure 2.5 are not blurred by the statistical nuance of the IV.

Evidently, both conditional effects are important in the model. The slopes of the lines represent the conditional effect of age; i.e., the horizon effect. All five lines slope downward, indicating an age-related decline in $\phi$ near retirement that does not come from the effect of wealth. The horizon effect is particularly strong after age 55 in the model. At the very end of working life, $\phi$ for all quintiles drops towards zero. The gaps between the lines for different wealth quintiles represent the conditional effect of wealth; i.e., the buffer-stock effect. The monotonicity of $\phi$ in wealth is clear, except at the very end of working life. The buffer-stock effect is quantitatively large: the transmission coefficient for households in the top wealth quintile is 30% to 50% smaller than the coefficient for households in the bottom quintile, conditional on age before age 55.

2.6 Conclusion

From the data I find that there is substantial heterogeneity across households in the response of nondurable consumption to long-lasting income shocks. In the face of labor-income shocks that last through at least three years, households with older heads adjust consumption by much less. Households with more liquid wealth also adjust consumption by much less. A calibrated version of the life-cycle incomplete markets model produces consumption responses that are quantitatively similar with regard to age and wealth heterogeneity to those estimated from the data. This is achieved
From high $\phi$ to low $\phi$: bottom quintile to top quintile in working-life distribution of wealth-to-income ratio

jointly by the buffer-stock effect, inherent in the incomplete markets assumption, and the horizon effect, generated from the life-cycle assumption.

What do these results mean for future research? First, it could be useful to verify these findings using panel data from countries other than the United States: Italy, Spain and the United Kingdom all provide data suitable for a similar exercise.

Second, the results in this paper imply significant cross-sectional heterogeneity among US households in the ability to self-insure. To the extent that the optimal design of public insurance depends on self-insurance capabilities, these results will be relevant for optimal policy in the cross-section. For example, policies concerned with long-term income maintenance for groups with a high ability to self-insure are not likely to provide significant welfare gain. In this regard, the verification of the life-cycle incomplete markets model that I offer here implies that the model is suitable for analyzing or designing age-dependent or means-tested public insurance policies and taxes.
References


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Appendix

2.A Performance of Estimator for $\phi$ under Measurement Error, Long-run Mean-reversion, and History Dependence

The estimator for $\phi$ obtained in Section 3.2 is robust to classical measurement errors in consumption and income. The estimator will be misspecified when $\rho < 1$; i.e. when there is mean-reversion in the long-lasting random component of log income. Nevertheless, a simple Monte-Carlo analysis of the estimator shows that when $\rho$ is close to one, the estimator performs reasonably well despite mean-reversion in the income process. The estimator will also be misspecified when consumption growth correlates with past income shocks (history dependence), as discussed in KV2010. However, the resulting bias is quantitatively small in the age profile of $\phi$ for the calibrated model in this paper.

The reason why the estimator for $\phi$ is robust to classical measurement errors is clear: since classical measurement error in log income is akin to transitory income shocks, it is not correlated with $g_t(y_t)$, which picks up only long-lasting changes in observed log income. On the other hand, classical measurement error in the dependent variable (log consumption) does not harm estimation, for the usual reason. By the
same logic, the estimator for $\phi$ is also robust to measurement errors that are MA(1).

When there is mean-reversion in the long-lasting income shock ($\rho < 1$), the estimator for $\phi$ will be misspecified:

$$\frac{\text{cov}(\Delta c_{it}, g^f_t(y_i))}{\text{cov}(\Delta y_{it}, g^y_t(y_i))} = \frac{\text{cov}(\Delta c_{it}, \rho^2 \eta_{it} + \rho \eta_{it+1} + \eta_{it+2} + (\rho^3 - 1) z_{it-1} + \varepsilon_{it+2} - \varepsilon_{it-1})}{\text{cov}(\Delta y_{it}, \rho^2 \eta_{it} + \eta_{it+2} + \rho \eta_{it+1} + \rho^3 \eta_{it-1} + \rho^4 \eta_{it-2} + (\rho^5 - 1) z_{it-3} + \varepsilon_{it+2} - \varepsilon_{it-3})} = \frac{\text{cov}(\rho (\eta_{it-1} + \rho \eta_{it-2} + \rho^2 z_{it-3}) + \eta_{it} + \Delta \varepsilon_{it}, \eta_{it+2} + \rho \eta_{it+1} + \rho^2 \eta_{it} + \rho^3 \eta_{it-1} + \rho^4 \eta_{it-2} + (\rho^5 - 1) z_{it-3} + \varepsilon_{it+2} - \varepsilon_{it-3})}{\rho^2 \text{cov}(\Delta c_{it}, \eta_{it})}$$

$$= \frac{\text{var}(\eta_{it}) + (1 - \rho) [(1 - \rho^2) \text{var}(z_{it-3}) - \rho \text{var}(\eta_{it-1}) + \rho^2 \text{var}(\eta_{it-2})]}{\text{cov}(\eta_{it}, \Delta c_{it})} = \frac{\text{var}(\eta_{it}) + (1 - \rho) [\text{var}(z_{it-3}) - \rho \text{var}(z_{it-1})]}{\text{cov}(\eta_{it}, \Delta c_{it})}$$

This type of misspecification bias will depend on the age of agents. When the variation in the initial condition for $z$ is not too small and $\rho$ is not too close to 1, $\text{var}(z_{it-3})$ will be larger than $\rho \text{var}(z_{it-1})$, and there will be a downward bias in the estimation of $\phi^n$. If, however, $\text{var}(z_{it-3}) < \rho \text{var}(z_{it-1})$, for example when initial variation in $z$ is small and variance of the $z$ component is quickly accumulating from $t - 3$ to $t - 1$, there will be an upward bias in the estimation of $\phi^n$. In both cases, the bias will be small if $\rho$ is reasonably close to 1.

A simple Monte Carlo experiment illustrates the pattern of bias in $\hat{\phi}$ when $\rho < 1$.

The income process in (1) is parameterized with $T = 40$, $\text{var}(z_{i0}) = 0.15$, $\text{var}(\varepsilon_{it}) = 28$

28 If measurement errors are systematic, then the estimator here might not perform well. However, for such systematic measurement errors to affect the heterogeneity result in this paper, it must be the case that certain groups (old, high liquid wealth) over-report income changes and/or under-report consumption changes, while other groups (young, low liquid wealth) under-report income changes and/or over-report consumption changes.

29 Measurement errors, however, will bias down estimates of consumption response to transitory income shocks, since typical measurement errors in income will be observationally equivalent to transitory income shocks. This is why I do not focus on transitory income shocks.
0.05, $\theta = 0.10$. To isolate the effect of income mean-reversion, I assume a log-linear consumption policy $\Delta c_{it} = \phi \eta_{it}$ with $\phi = 0.5$, so that consumption orthogonality conditions are satisfied. The income process is simulated for 50000 households in each experiment. I repeat the experiment 200 times for each of the following values of $\rho$: 1, 0.99, 0.97, 0.93, and set $\text{var}(\eta_{it})$ in each case such that $\text{var}(z_{iT}) = 0.55$.

Figure 1 plots the average estimate of $\phi$ at each time $t$. The lines from top to bottom correspond to different true value of $\rho$. The absolute value of the bias in $\hat{\phi}$ when $\rho < 1$ is smaller than 0.05 in all cases. Age specificity of the bias is concentrated before age 35, and is also small in magnitude.

The estimator will also be misspecified if consumption growth is correlated with past income shocks (history dependence of consumption). KV2010 point out that in simulated data generated by the life-cycle incomplete markets model, the IV estimator overestimates consumption responses for households near the borrowing limit. In the model, constrained households who receive negative transitory shocks are forced to consume much of the shock, but they will expect consumption growth in the future as the shock wears off. This creates a negative correlation between consumption growth...
and lagged transitory income shocks, which violates the orthogonality conditions of the IV estimator. With potentially non-zero \( \text{cov}(\Delta c_{it}, \varepsilon_{it-1}) \) in the model, the previous expression for the IV estimator becomes

\[
\frac{\text{cov}(\Delta c_{it}, g_t^c(y_i))}{\text{cov}(\Delta y_{it}, g_t^q(y_i))} = \frac{\text{cov}(\eta_{it}, \Delta c_{it}) - \rho^{-2} \text{cov}(\Delta c_{it}, \varepsilon_{it-1})}{\text{var}(\eta_{it}) + (1 - \rho) \left[ \text{var}(z_{i,t-3}) - \rho \text{var}(z_{i,t-1}) \right]}.
\] (2.10)

Since in the model \( \text{cov}(\Delta c_{it}, \varepsilon_{it-1}) < 0 \) for constrained agents, the model IV estimates will contain an additional upward bias. Figure 2.7 plots the age profile of \( \phi \) estimated by the IV estimator against the age profile of true consumption responses in the calibrated life-cycle incomplete markets model as in Section 5 in the main text. The differences between the true and the IV estimated transmission coefficients in the model come from both mean-reversion (\( \rho = 0.964 \)) and history dependence of consumption. As can be seen in Figure 2.7, the upward bias of the IV estimator in the age profile of \( \phi \) is quantitatively small in the calibrated model. The bias in the age profile of \( \phi \) shows up mainly before age 40, when more of the households are constrained in the model.

2.B Appendix Table

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Variable</th>
<th>Estimate</th>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln c</td>
<td>0.970</td>
<td>Age^2</td>
<td>-0.000349</td>
<td>Born 1955-59</td>
<td>-0.0825</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td></td>
<td>(0.000575)</td>
<td></td>
<td>(0.0581)</td>
</tr>
<tr>
<td>ln c × high school grad</td>
<td>-0.0294</td>
<td>Northeast</td>
<td>0.0325</td>
<td>Born 1950-54</td>
<td>-0.112</td>
</tr>
<tr>
<td></td>
<td>(0.0260)</td>
<td></td>
<td>(0.00527)</td>
<td></td>
<td>(0.0529)</td>
</tr>
<tr>
<td>ln c × college or above</td>
<td>-0.232</td>
<td>Midwest</td>
<td>0.00522</td>
<td>Born 1945-49</td>
<td>-0.164</td>
</tr>
<tr>
<td></td>
<td>(0.0271)</td>
<td></td>
<td>(0.0111)</td>
<td></td>
<td>(0.0481)</td>
</tr>
<tr>
<td>ln c × year-1980</td>
<td>-0.00418</td>
<td>South</td>
<td>0.0149</td>
<td>Born 1940-44</td>
<td>-0.177</td>
</tr>
<tr>
<td></td>
<td>(0.000374)</td>
<td></td>
<td>(0.0114)</td>
<td></td>
<td>(0.0438)</td>
</tr>
<tr>
<td>ln c × one child</td>
<td>0.0964</td>
<td>Family size</td>
<td>0.0700</td>
<td>Born 1935-39</td>
<td>-0.179</td>
</tr>
<tr>
<td></td>
<td>(0.0368)</td>
<td></td>
<td>(0.0176)</td>
<td></td>
<td>(0.0389)</td>
</tr>
<tr>
<td>ln c × two children</td>
<td>0.123</td>
<td>ln p_{food}</td>
<td>-0.789</td>
<td>Born 1930-34</td>
<td>-0.179</td>
</tr>
<tr>
<td></td>
<td>(0.0381)</td>
<td></td>
<td>(0.101)</td>
<td></td>
<td>(0.0340)</td>
</tr>
<tr>
<td>ln c × three children+</td>
<td>0.165</td>
<td>ln p_{transports}</td>
<td>0.475</td>
<td>Born 1925-29</td>
<td>-0.186</td>
</tr>
<tr>
<td></td>
<td>(0.0315)</td>
<td></td>
<td>(0.113)</td>
<td></td>
<td>(0.0302)</td>
</tr>
<tr>
<td>One child</td>
<td>-0.858</td>
<td>ln p_{fuel+utilis}</td>
<td>-0.878</td>
<td>Born 1920-24</td>
<td>-0.195</td>
</tr>
<tr>
<td></td>
<td>(0.349)</td>
<td></td>
<td>(0.0918)</td>
<td></td>
<td>(0.0263)</td>
</tr>
<tr>
<td>Two children</td>
<td>-1.072</td>
<td>ln p_{alcohol+tobacco}</td>
<td>-0.716</td>
<td>Born 1910-19</td>
<td>-0.113</td>
</tr>
<tr>
<td></td>
<td>(0.372)</td>
<td></td>
<td>(0.121)</td>
<td></td>
<td>(0.0225)</td>
</tr>
<tr>
<td>Three children+</td>
<td>-1.516</td>
<td>ln p_{cpi}</td>
<td>2.656</td>
<td>White</td>
<td>0.0899</td>
</tr>
<tr>
<td></td>
<td>(0.310)</td>
<td></td>
<td>(0.287)</td>
<td></td>
<td>(0.0177)</td>
</tr>
<tr>
<td>High school grad</td>
<td>0.242</td>
<td>Born 1970-74</td>
<td>0.0151</td>
<td>Constant</td>
<td>-2.009</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
<td></td>
<td>(0.0758)</td>
<td></td>
<td>(1.036)</td>
</tr>
<tr>
<td>College and above</td>
<td>2.099</td>
<td>Born 1965-69</td>
<td>-0.0180</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.241)</td>
<td></td>
<td>(0.0694)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.0410</td>
<td>Born 1960-64</td>
<td>-0.0489</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00536)</td>
<td></td>
<td>(0.0637)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports detailed demand system estimates used in the imputation of nondurable expenditure in the PSID sample. The left-hand side variable is log nominal food expenditure. Right-hand side variables are log real nondurable expenditure plus interactions, demographic controls and price levels. I instrument log real nondurable expenditure (and their interactions) with the cohort-year specific average of the log husband’s and wife’s hourly real wage rates (and their interactions with age, education, and a time trend) as per recommendations in Campos and Reggio (2014). The standard errors are in parentheses. The p-value from both the F test of excluded instruments and the Angrist-Pischke multivariate F test of excluded instruments is smaller than 0.0001 for all endogenous variables.
Figure 2.7: Performance of IV Estimator $\hat{\phi}$ in the Calibrated Model
Chapter 3

Does Monetary Easing Lead to Differential Credit Responses?
Evidence from Chinese Loan-level Data

3.1 Introduction

Pervasive monetary policy actions around the world have led to increasing demand in understanding monetary policy’s consequences and effects. Over and beyond the canonical aggregate effects, an active program has formed on the research frontier focusing on the redistributive channel, or whether monetary policy “picks winners and losers” as Hall and Lieberman (2012) have put it. While this program has led important empirical discoveries in the context of the U.S. as well as selected other developed economies, much less is known about it in the context of less-developed economies, which make up an increasingly large share of the world economy.
In this paper, we fill this gap by studying the redistributive effect of monetary policy in a large developing economy. Our analysis takes advantage of a rich data set on bank lending in China covering loan-level information on all commercial loans made by a major national bank, accounting for approximately 10% of all corporate lending in China. This loan-level data set covers a broad spectrum of borrowing firms, with detailed information on both loan characteristics and firm types. We use this data set to study the credit channel of monetary transmission in China, namely how monetary policy easing loosens conditions in the credit market, and explore how the effect of monetary policy easing differs across firms of different types.

Our analysis focuses on three dimensions of heterogeneity: size, riskiness, and ownership type. Our attention on size and riskiness are motivated by two influential empirical findings in this literature in the developed economy context, (1) the “excess sensitivity” to monetary policy, that smaller, more financially constrained firms, through bank credit, are more responsive to monetary policy, as in Gertler and Gilchrist (1994), and (2) the “risk-taking channel” of monetary policy, that monetary easing leads to more bank credit to risky firms, as in Jiménez et al. (2014) and Dell’Ariccia et al. (2017). Our attention on firm ownership type is motivated by the perceived systematic biases in bank lending along this dimension, whereby state-owned enterprises are thought to face more favorable terms compared to private firms, as in Boyreau-Debray and Wei (2005) and Song et al. (2011).

The basic question that the analysis seeks to answer is the following: when credit market easing happens in China, how does this manifest itself in terms of the changes in the amount of loans and interest rates on these loans, and how do these changes differ across the different firm types. Do small firms benefit more when more credit becomes available? Does the extra credit go to firms that are relatively risky? Or is the increase in credit allocated disproportionately to state-owned enterprises?
To deal with the challenge that underlying changes in the economic condition (absent the monetary policy change) could confound the estimation of the effect of monetary easing, our empirical strategy focuses on the narrow time windows before and after monetary policy announcements, which we take to be 30 days before and after. Our identification assumption is that within this narrow time windows, the effect of monetary easing is discrete, while the underlying economic condition is relatively constant, allowing us to recover the response in the price and quantity of credit to monetary easing. In principle, the method used in this paper could be applied to study the effects of both monetary easing and monetary tightening, but given that the period of our data contains only monetary easing events, our analysis focus on the effect of monetary easing.

In our main results, we find that smaller firms (in terms of registered capital) and firms with lower risk ratings do benefit more. Moreover, the effect is concentrated in larger increases in the size of new loans, as opposed to lower interest rates or more favorable maturities. We also find that systematically-favored state-owned firms do not benefit disproportionately more, contrary to common perceptions.

The finding that credit tends to flow to smaller firms in monetary easing is supportive of the “excess sensitivity” hypothesis of Gertler and Gilchrist (1994). But the finding that the additional credit goes disproportionately to less risky firms contrasts with previous findings on the “risk-taking channel” of monetary policy in developed economy contexts. Indeed, our results suggest that the nature of the relationship between monetary policy and risk-taking can be complex and context-dependent.

Our analysis also contributes to the study of monetary policy transmission, especially how it might differ depending on the level of development in the economy and the capital markets. Our results provide loan-level evidence of the quantitative-based nature of monetary policy transmission in China as opposed to price-based. Our results, together with the aggregate time-series findings on the quantitative nature
of the monetary policy rules in Chen et al. (2016), serves to clarify channels through which monetary policy operates in economies with developing capital markets.

The remainder of the paper is organized as follows. Section 3.2 describes the institutional background on China’s monetary system and bank lending to firms. Section 3.3 introduces our loan-level data and discusses the empirical strategy. The main empirical results are reported in Section 3.4. Section 3.5 concludes.

3.2 Institutional Background

This section provides institutional details and highlights institutional differences relevant for understanding the two key elements of our exercise, monetary policy and bank lending to firms, in the context of the developing economy of China, with a focus on our sample period of 2012 to 2016.

3.2.1 Monetary policy in China

Monetary policy in China is conducted by the People’s Bank of China (the central bank of China, or the PBC in short). To achieve the monetary policy goals including maintaining price stability, boosting economic growth, promoting employment, and broadly maintaining the balance of payments, the PBC make use of a mixture of quantity-based and price-based monetary policy instruments, including open market operations, the required reserve ratio, and the benchmark deposit/lending interest rates. As discussed in Chen et al. (2016), distinct from most developed economies, the interbank market interest rate is not the intermediate target of the PBC. Following this, changes in the targeted interbank rate reflect mainly market fluctuations and are not the primary gauge of the monetary policy stance.

Instead, PBC announcements on changes in the required reserve ratio and the benchmark interest rates (guideline interest rates on deposits and loans) have long
served as the headline monetary policy events in China. Announcements on changes in the required reserve ratio and the benchmark interest rates are infrequent. During our sample period of 2012 to 2016, we observe only 13 such announcements. They also come with no set schedules (unlike for example the set schedules for FOMC meetings and federal funds rate changes in the US), making these monetary policy announcements not easily forecastable.

The monetary policy announcements on changes in the required reserve ratio and the benchmark interest rates lead to large, discrete impact on credit market conditions. The credit market impact comes in direct and indirect ways. Directly, changes in the required reserve ratio alter the amount of loanable fund at Chinese banks, which rely heavily on deposit funding. The interbank market for loanable funds does not dampen the impact of the changes in the required reserve ratio, as the required reserve ratio applies to the banking sector as a whole as well as individual banks. Changes in the benchmark interest rates alter the cost of funding for borrowers as Chinese banks follow the benchmark interest rates closely in loan pricing. \(^1\)

Indirectly, a downward adjustment of the required reserve ratio and the benchmark interest rates signals that the PBC is willing to accommodate faster credit growth through an upward adjustment in its credit growth targets which, importantly, are not publicly announced. This indirect implication also de-emphasizes the literal meaning of the numerical changes in the required reserve ratio and/or the benchmark interest rates, but rather stresses that these monetary policy announcements represent policy events. Indeed, the fact that the numerical adjustments do not represent the credit market impact of the monetary policy announcements fully play an important role in

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1The close relationship between bank loan rates and the benchmark lending interest rates started in the era of interest rate regulation in China. Before 1982, banks in China are required to strictly adhere to the PBC benchmark lending interest rates in lending. After 1982, the government has gradually relaxed this requirement, allowing interest rate on loans to first float within a narrow range around the benchmark rates, with the range gradually relaxed in the late 1990s and the early 2000s, and eventually abolished in July of 2013. Even though interest rate control is now history, the benchmark interest rates still play a strong influence over banks through PBC window guidance and coordination.
guiding us to focus on estimating the credit response following an *average* monetary policy event in Section 3.3 and Section 3.4.

During our sample period of 2012 to 2016, the PBC cut the required reserve ratio 8 times and the benchmark interest rates 8 times, in response to deflationary pressures and lackluster economic growth. Indeed, the producer price index declined relative to the same month previous year in all but 6 months of the sample period, and the GDP growth rate during the period was comparable only to levels in the 1997 Asian financial crisis and the 2008-2009 global financial crisis. During the period, the required reserve ratio dropped from 21% in the beginning of 2012 to 17% at the end of 2016, and the benchmark interest rate on one year loans dropped from 6.56% to 4.35% during the same period. Among the aforementioned monetary policy announcements, there were 3 in which both monetary policy instruments were adjusted simultaneously. All adjustments in the required reserve ratio and in the benchmark interest rates were downward adjustments, marking these as all monetary easing events.

### 3.2.2 Bank Lending to Firms

Our focus on bank lending and the credit channel of monetary policy are two-fold. First, the monetary policy announcements we consider concerns monetary policy actions designed primarily to work through influencing credit market conditions. Second, the economy under study is one strongly dominated by bank financing. Indeed, bank dominance is a shared feature of financial systems in developing markets, as discussed in Allen et al. (2012). Two potential reasons for the association between developing economies and bank-dominated financial markets are worse public information on borrowers, following Dang et al. (2013), and the more significant comparative advantage of banks over individual investors in monitoring and information collection in informationally-scarce environments, following De Fiore and Uhlig (2011).
We furthermore focus on bank lending to firms because non-financial corporate loans make up the largest component of bank credit and even overall external financing in China. In fact, according to PBC statistics at the end of 2016, bank lending to non-financial corporates dominates the combination of domestic non-financial corporate equity, domestic non-financial corporate bonds, as well as households bank credit. Indeed, this makes bank lending to firms a priori the most important component of the monetary transmission mechanism in China.

In addition to the differentiation across firms of different size and riskiness, we focus on comparing firms of various ownership types. This dimension of comparison is motivated by the perceived systematic biases across state-owned firms and non-state-owned firms, as suggested in Song et al. (2011). In particular, the biases work for generally less-productive state-owned enterprises (SOEs), and work against private firms, potentially lead to misallocation of funding across firms. Indeed, in Section 3.3, we provide loan-level empirical evidence of lending biases favoring these state-owned enterprises.

The cross-section biases notwithstanding, it is not certain whether monetary easing would channel disproportionately more funding to favored versus underserved firms, in this case state-owned enterprises versus private firms. In fact, the theoretical literature suggests ambiguous effects. On the one hand, the canonical Gertler and Gilchrist (1994) logic suggests that the more constrained private firms should benefit disproportionately more to a market-wide loosening of credit conditions. On the other hand, Liu et al. (2017) recently describes a framework in which the systematic lending bias towards state-owned firms make credit market loosening disproportionately beneficial for the favored state-owned firms. We believe there is no a priori theoretical reason why the effect has to go one way or the other; different modeling of the credit constraints can lead to different predictions. In this regard, the empirical exercise in this paper might provide moments that help guide modeling of the credit constraints.
Finally, the incentive and capacity for banks in managing loan risks in developing credit markets such as China can be quite different than more developed credit markets. Indeed, there is a lack of securitization in China, which means that originating banks have to keep the loan risks on its balance sheet longer. Furthermore, with worse enforcement and collection systems, incentives in the loan-making process could be very different. Both of these effects make banks potentially more cautious in lending following monetary easing.

Taken as a whole, the institutional differences suggests that the credit response to monetary easing in developing credit markets is an open empirical question. In the next section, we illustrate how we make use of a rich data set on bank lending from China to address this gap in our understanding of monetary policy transmission.

### 3.3 Data and Empirical Strategy

In this section, we describe the data set on bank lending, and how we deal with the empirical challenges to estimate the credit responses following monetary policy announcements.

#### 3.3.1 Data

We exploit a comprehensive loan-level data set from one of the largest state-owned national banks in China, which represents 10% of the total commercial loan in China by loan amount and has branches in more than 300 cities in China. State-owned national banks play an important role in China. According to the annual report of China Banking Regulatory Commission, there are 4262 banking institutions by the end of 2015, which include three policy banks, five state-owned national banks, twelve national joint-stock commercial banks, and thousand of local banks. However, 39.2% of the total asset in banking sectors belongs to the five state-owned national banks.
We obtain information from this bank that covers all loans to corporate borrowers from this bank over the 2012 to 2016 period. To facilitate our empirical exercise, we select loans with no missing information on loan terms and borrower characteristics. Our final sample amounts to 762,697 loans made by this bank to corporate borrowers during this 5 year period.

Our loan-level data set provides detailed information on the loans and the characteristics of the borrower firms. Table 3.1 provides a summary of our data set. In addition to the approval date of the loan (APPROVE DATE) and the loan size (CREDIT AMOUNT), we observe the interest rate (LOAN RATE) in the case of fixed-rate loans, and the interest rate multiple (RATE MULTIPLE) in the case of adjustable-rate loans, as well as the loan maturity (MATURITY). It is interesting to note that interest rates on adjustable-rate loans in China are set to be a fixed multiple of a benchmark interest rate. We also observe a wide array of borrower characteristics, including ownership type, number of employees (EMPLOYEES), whether the firm is listed on a stock market (LISTED FIRM), registered capital of the firm (REGISTERED CAPITAL), the amount of deposits the firm keeps at this bank (DEPOSITS), and the internal risk rating that this bank assigns to the firm (INTERNAL RISK RATING).
Table 3.1: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Q1</th>
<th>Median</th>
<th>Q3</th>
<th>Max</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CREDIT AMOUNT(_{it})</td>
<td>15,900,000</td>
<td>1,000</td>
<td>1,500,000</td>
<td>4,000,000</td>
<td>10,000,000</td>
<td>19,000,000,000</td>
<td>66,500,000</td>
</tr>
<tr>
<td>LOAN RATE(_{it})</td>
<td>6.93%</td>
<td>0.00%</td>
<td>6.16%</td>
<td>6.90%</td>
<td>7.50%</td>
<td>28.20%</td>
<td>1.88%</td>
</tr>
<tr>
<td>RATE MULTIPLE(_{it})</td>
<td>108.33%</td>
<td>40.00%</td>
<td>100.27%</td>
<td>101.40%</td>
<td>115.00%</td>
<td>258.29%</td>
<td>13.60%</td>
</tr>
<tr>
<td>MATURITY(_{it})</td>
<td>20.66</td>
<td>1</td>
<td>13</td>
<td>15</td>
<td>18</td>
<td>576</td>
<td>27.64</td>
</tr>
<tr>
<td>SOE(_{it})</td>
<td>0.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collective(_{it})</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private(_{it})</td>
<td>0.67</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HKMacauTaiwan(_{it})</td>
<td>0.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign(_{it})</td>
<td>0.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other(_{it})</td>
<td>0.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMPLOYEES(_{it})</td>
<td>1,059.83</td>
<td>1</td>
<td>50</td>
<td>120</td>
<td>340</td>
<td>2,000,000</td>
<td>14,176.47</td>
</tr>
<tr>
<td>LISTED FIRM(_{it})</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>REGISTERED CAPITAL(_{it})</td>
<td>6,530,000,000</td>
<td>1</td>
<td>3,000,000</td>
<td>10,000,000</td>
<td>50,000,000</td>
<td>1,036,000,000,000</td>
<td>52,400,000,000</td>
</tr>
<tr>
<td>DEPOSITS(_{it})</td>
<td>25,300,000</td>
<td>0.00</td>
<td>78,813.30</td>
<td>1,110,000</td>
<td>6,650,000</td>
<td>19,800,000,000</td>
<td>169,000,000</td>
</tr>
<tr>
<td>INTERNAL RISK RATING(_{it})</td>
<td>4.61</td>
<td>0</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>17</td>
<td>3.13</td>
</tr>
<tr>
<td>RRR(_t)</td>
<td>19.0%</td>
<td>17.0%</td>
<td></td>
<td></td>
<td></td>
<td>21.0%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Benchmark Rate(_t)</td>
<td>5.50%</td>
<td>4.35%</td>
<td></td>
<td></td>
<td></td>
<td>6.56%</td>
<td>0.79%</td>
</tr>
</tbody>
</table>
The complete coverage of corporate loans make our data a unique opportunity in examining bank lending to all of large, medium-sized, and small firms. The loan size in our data set ranges from as large as 19 billion yuan (approximately 3 billion US dollars) to as small as one thousand yuan (approximately 150 US dollars). The loan amount distribution is strongly right-skewed, with the median loan at 4 million yuan, substantially below the average loan amount of 15.9 million yuan. The size of the borrowing firms also ranges from very large to very small. We adopt two measures of firm size: the number of employees and the amount of registered capital. The firms in our sample employ anywhere between 1 employee and 2 million employees, and half of the loans in our sample are made to firms employing 120 workers or less. The registered capital is a legal concept in China corresponding to both the amount of funding that the shareholders have pledged in the firm and the maximum liability the firm is legally required to repay on unsecured loans. There are large variations in the registered capital as well, with one-quarter of the loans made to firms with registered capital less than 3 million yuan (equivalent to slightly less than 500,000 dollars) and the largest registered capital at over 1 trillion yuan. In China, firms with less than 200 employees or a registered capital amount smaller than 100 million yuan fall into the category of small and medium-sized enterprises (SMEs). Overall, SMEs contribute to more than three-quarters of the loan data in our sample.

Indeed, our coverage of small and medium-sized loans and loans to SMEs, which make up a dominating majority of loans in the sample, makes our data set a unique opportunity in examining external financing a wide spectrum of firms in the economy. Other data sources on bank lending do not provide nearly as good coverage outside large firms or loans. For example, loans to listed firms, which are covered also in public financial reports, accounts for only 3% of loans in our data set. As another example, banks are required to report to the Chinese Banking Regulatory Committee (or the CBRC in short) loans with a committed size above 50 million yuan (approximately
7 million US dollars). Meanwhile, more than three quarters of the loans in our data are below this 50 million yuan cutoff for reporting to the CBRC, making our data set uniquely suitable for analyzing lending to a wide spectrum of borrowing firms in terms of size.

Moving to other loan characteristics, we note that fixed-rate loans account for 43% of the loans in our sample. The interest rate on fixed-rate loans, represented by the variable LOAN RATE, are distributed with a high kurtosis, with the majority of the loans at interest rates between 6% to 8%, plus some very far in the left and right tails.

Adjustable-rate loans account for the rest of the loans, which amounts to 57% of loans in our sample. The variable RATE MULTIPLE represents the fixed ratio between the interest rate on the loan and the (time-varying) benchmark borrowing interest rate set by the central bank. What this means is that even though the benchmark borrowing interest rate is not obligatory *de jure*, our bank follows the benchmark borrowing interest rate *de facto* for adjustable-rate loans.

The average loan maturity in our data set is 21 months. The sample bank lend as short-term as 1 month, and as long-term as 48 years, but the majority of loans matures between one or two years.

Across types of firm ownership, most of the loans in our dataset are in fact made to domestic private enterprises, which amounts to 67% of the sample by the number of loans. In comparison, state-owned enterprises account for 9% of the loans. However, as we will show later in this section, loans to state-owned enterprises are much larger. The rest of the loans are made to firms that are collectively-owned (township and village enterprises), firms owned by persons or entities in Hong Kong, Macau, or Taiwan, foreign-owned firms, and firms labeled as the unclassified ownership type.

The bank assigns an internal risk rating from 0 to 17 for its customers, 0 indicative of the least risk and 17 indicative of the most risk. For each value from 0 to 17, there
are firms being assigned to that value in the bank’s risk rating. Finally, the borrowing firms in our sample keep substantial deposits at this bank, often at the same order of magnitude to the loans that they take out, potentially increasing the efficacy of monitoring by the bank on the borrowing firms, following the idea in Fama (1985).

Before turning to monetary policy’s impact on price and quantity of credit for firms with different characteristics, we explore how price, quantity and maturity of credit depend on firm size, firm risks, and firm ownership type on average in the cross-section. We run in the pooled sample OLS regression of the dependent variables, which are log of credit amount, level of interest rate on fixed-rate loans, interest rate multiples on adjustable-rate loans as well as loan maturity, on firm types as independent variables, which include firm size measures, risk rating, firm ownership type, and amount of deposits at this bank.

We report the cross-sectional relationship between price, quantity and maturity of credit and firm characteristics in Table 3.2.

The coefficients on the ownership dummies in the first five rows represent differences compared to state-owned enterprises (SOEs). What we find in our loan-level data is that compared to SOEs with similar risk ratings and other observable characteristics, private firms and township and village enterprises (TVEs, which are collectively-owned) get smaller loans, on average 36% smaller for private firms, and at higher interest rates, on average 49 basis points higher for private firms on fixed-rate loans. Firms owned by entities outside mainland China, including foreign firms, get smaller loans compared to SOEs ceteri paribus, but they get lower interest rates on adjustable-rate loans and do not consistently get different rates than SOEs on fixed-rate loans. Firms with the unclassified ownership type (“Other”) looks similar to private firms in that they get smaller loans at higher interest rates. Non-SOEs also borrow substantially more short-term than SOEs, with loan maturity on average over 20 months shorter than otherwise similar SOEs. Listed firms get marginally
Table 3.2: How do Characteristics Affect Credit Price and Quantities in the Cross-Section

<table>
<thead>
<tr>
<th></th>
<th>LN(CREDIT AMOUNT) (_{it})</th>
<th>LOAN RATE (_{it})</th>
<th>RATE MULTIPLE (_{it})</th>
<th>MATURITY (_{it})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collective (_i)</td>
<td>-0.44***</td>
<td>0.49***</td>
<td>0.97***</td>
<td>-20.9***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.31)</td>
<td>(1.5)</td>
</tr>
<tr>
<td>Private (_i)</td>
<td>-0.62***</td>
<td>0.64***</td>
<td>0.75***</td>
<td>-24.3***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.17)</td>
<td>(1.3)</td>
</tr>
<tr>
<td>HKMacauTaiwan (_i)</td>
<td>-0.49***</td>
<td>0.30***</td>
<td>-1.50***</td>
<td>-20.4***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.11)</td>
<td>(0.24)</td>
<td>(1.4)</td>
</tr>
<tr>
<td>Foreign (_i)</td>
<td>-0.52***</td>
<td>0.11</td>
<td>-2.25***</td>
<td>-20.3***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.26)</td>
<td>(1.4)</td>
</tr>
<tr>
<td>Other (_i)</td>
<td>-0.98***</td>
<td>0.68***</td>
<td>1.53***</td>
<td>-23.1***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.12)</td>
<td>(0.26)</td>
<td>(1.4)</td>
</tr>
<tr>
<td>LN(EMPLOYEES)</td>
<td>0.07***</td>
<td>-0.07***</td>
<td>-1.00***</td>
<td>-2.51***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>LN(REGISTERED CAPITAL)</td>
<td>0.27***</td>
<td>-0.02***</td>
<td>-0.95***</td>
<td>2.96***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>ListedFirm (_it)</td>
<td>0.06</td>
<td>-0.12**</td>
<td>-0.31</td>
<td>-7.21***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.28)</td>
<td>(0.82)</td>
</tr>
<tr>
<td>LN(DEPOSITS)</td>
<td>0.03***</td>
<td>-0.07***</td>
<td>-0.14***</td>
<td>0.12**</td>
</tr>
<tr>
<td></td>
<td>(0.1)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>INTERNAL RISK</td>
<td>-0.08***</td>
<td>0.05***</td>
<td>0.61***</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>N</td>
<td>762697</td>
<td>330998</td>
<td>431699</td>
<td>625566</td>
</tr>
<tr>
<td>Adjusted-R(^2)</td>
<td>0.27</td>
<td>0.07</td>
<td>0.13</td>
<td>0.13</td>
</tr>
</tbody>
</table>

**Note:** This table shows the cross-sectional regression results of price and quantity of credit on firm characteristics in the pooled sample. For each variable the first row lists the coefficient, the second row lists the standard error that is corrected for clustering at the year-month and firm level; the corresponding significance levels are adjacent to the coefficient.
larger loans at lower interest rates according to the point estimates, but these effects are not statistically significant except for the lower interest rate on fixed-rate loans. Our cross-sectional results on ownership in the loan-level data are consistent with the perception of systematic lending biases that makes it easier for SOEs on average to obtain credit than private firms.

As expected, firms with higher risk rating get lower loan amounts at higher interest rates and slightly shorter maturities. The point estimates suggest that a one standard deviation increase in the risk rating is associated with a 24% decrease in the loan amount, a 15 basis point higher interest rate for a fixed-rate loan, a 2 percentage point higher interest rate multiple for an adjustable-rate loan, and on average two weeks shorter in loan maturity.

Turning to our measures of firm size, we find that firms with either more employees or with a higher registered capital get larger loans at lower interest rates, holding constant other factors including the risk rating. The relationship between loan maturity and firm size measures is more complex. Firms with higher registered capital borrows more long term, consistent with the idea that they face easier credit conditions. However, firms with a larger number of employees borrow more shorter, holding fixed registered capital, potentially reflecting stronger short-term funding needs for labor-intensive firms. Finally, more deposit holding at this bank is also associated with qualitatively similar effects.

After getting a sense of the cross-sectional relationship between the price and quantity of credit and firm characteristics, we now return to this paper’s main objective, that is testing whether monetary policy leads to differential credit responses, in the price, quantity and maturity of credit, across firm size, firm risks, and firm ownership. We discuss the empirical challenges, our empirical strategy, and the associated the qualifications in the next subsection.
3.3.2 Empirical Challenges and Empirical Strategy

The obvious empirical challenge is that monetary policy is set in response to the underlying economic conditions, and the underlying economic conditions can confound the estimation of the effect of monetary policy. For example, it could be that a monetary easing is carried out when the underlying economic condition is worsening. In this case, the resulting price, quantity and maturity of bank credit to firms will be the combination of the worsening underlying economic condition and the effect of the monetary easing.

Our strategy for dealing with this empirical challenge exploits the discreteness of monetary policy. We estimate the credit response to monetary policy by comparing observations on new loans within a narrow time window before and after each monetary policy announcement. The identification assumption is a timing assumption, that the underlying economic condition absent the monetary policy change is relatively constant within this narrow time window, while the effect of the monetary policy change is discrete around the announcement date. In our implementation, we choose the time window to be 30 days before and 30 days after the monetary announcement date (Figure 3.1). As a consequence, our identification assumption amounts to that the underlying economic condition absent the monetary policy change is relative constant within this 60 days window.

Another empirical challenge is measurement of monetary policy. We have chosen to focus on the infrequent headline policy announcements by the PBC, in which it makes public the changes in the required reserve ratio, or in the benchmark interest rate, or in both. A choice has to be made whether to take the announced changes in the two policy instruments literally, and estimate the credit responses to the numerical changes in the policy instruments, or be more conservative, take the headline policy announcements as signals of changes in the PBC’s overall stance, and instead estimate the average credit responses to a monetary policy event. Officials to which we have
Note: This figure illustrates the event window for our estimation of the credit response to monetary policy announcements. We use observations on new loans made within 30 days before and 30 days after the monetary announcement date. As a consequence, our identification assumption amounts to that the underlying economic condition absent the monetary policy change is relatively constant within this 60 days window.

had discussions with and who are familiar with the monetary policy making process in China suggest that the headline policy announcements are usually accompanied by changes in credit growth ceilings the PBC sets for commercial banks, and that although these accompanied changes are not made public, their influences on the banks are often stronger than the headline changes in the required reserve ratio or the benchmark interest rates. This suggests that the latter approach makes more sense. Therefore we follow the latter approach in our main exercise.

Our baseline empirical strategy is represented by the following regression:

\[
Y_{it} = b_0 + (b_1 + b_2 * \text{Characteristics}_{it}) * \text{Post}_t \\
+ b_3 * \text{Characteristics}_{it} + \gamma_{\text{event}} + \epsilon_{it}
\]  

(3.1)  

(3.2)

where the sample for the estimation are all new loans made during the event windows surrounding the 13 monetary policy events in 2012-2016, which are monetary easing events as we discussed in Section 3.2.1. The dependent variables are the log of loan amount, the interest rate on fixed-rate loans, and the interest rate multiple on adjustable-rate loans. The term \text{Post}_t equals 1 if the loan is made after the monetary policy announcement in the event window, and 0 otherwise; this takes into account of
the monetary policy events in our sample period are all monetary easing events. The
term $\gamma_{\text{event}}$ represents event fixed effects that captures the changes in the underlying
economic conditions across different event windows. To allow for the possibility
that the changes in the underlying economic conditions could differ along observable
characteristics, we also consider the following regression with characteristics-dependent
event fixed effects:

$$Y_{it} = b_0 + (b_1 + b_2 \cdot \text{Characteristics}_{it}) \cdot \text{Post}_t$$

$$+ (b_3 + b_{\text{event}}) \cdot \text{Characteristics}_{it} + \gamma_{\text{event}} + \epsilon_{it}$$

where $b_{\text{event}}$ are event-specific coefficients capturing the characteristics-dependent event
fixed effects.

The coefficient $b_1$ represents the average credit response in our sample to monetary
easing: changes in the loan amount, or changes in the interest rates, before and after
the monetary easing announcements, after controls. The key object of interest in this
paper is the vector of coefficients $b_2$, which represents the differential credit response
in our sample to monetary easing: the differences across firm characteristics in the
changes in the loan amount, or changes in the interest rates, before and after the
monetary easing announcements, after controls.

Before turning to the results of estimating regressions (3.1) and (3.3), we would
like to put forward two comments about our estimation.

First, although our estimation controls for the underlying economic condition
surrounding each monetary policy event absent the monetary policy changes, the
estimated credit responses does not distinguish between the partial equilibrium (credit
supply) and the general equilibrium (credit demand) effects of the monetary policy
changes. This means that our results should not be interpreted as the differential
effect of credit supply expansions following monetary easing.  

Second, our estimates would not fully reflect the effect of monetary policy if
systematic changes in our sample bank’s across different borrowers are correlated with
monetary policy events. Although we are not aware of evidence suggesting this is the
case — detailed lending data covering multiple banks with borrower characteristics
would be needed for a direct test — we caution that our results should be interpreted
with this qualification.

We turn to the main results in the next section.

3.4 Empirical Results

This section reports the main result of the paper, the estimated regression for differen-
tial changes in loan amount and interest rates across firms of different characteristics
following monetary policy events, which during our sample period of 2012 to 2016 are
all monetary easing events.

3.4.1 Changes in Loan Amount following Monetary Policy

Events

Table (3.3) reports the regression results for the changes in loan amounts on new
loans before and after monetary policy events within the -30 days, +30 days window.
As reported in column (1), we find that loan amounts in our sample on average
increase 5% after a monetary easing event. After confirming that the monetary easing
increases loan amount overall, we turn to our main object of interest, the differential
changes across firm characteristics, which are shown in columns (2) and (3). Columns
(2) reports estimated results for our baseline regression (3.1). Columns (3) reports

\footnote{In this regard, our estimation follows more closely the broader definition of the credit channel in Bernanke (2007).}
estimated results for regression (3.3), where we further control for characteristic-dependent underlying economic conditions. The results on the differential responses are broadly similar across columns (2) and (3).

We find that firms with lower risk ratings experience larger increase in loan amounts following monetary easing. In terms of the economic magnitude, a one standard deviation decrease in the risk rating increases the response in the loan amount by 6 percentage points. This seems to be inconsistent with the risk-taking channel of monetary policy found in empirical studies using data from the developed countries.

In terms of firm size, we find that firms with lower registered capital experiences larger increase in loan amounts. However, number of employees is not consistently associated with differences in the response in loan amounts to monetary easing. Overall, this suggests that we find weak support of the “excess sensitivity” finding in Gertler and Gilchrist (1994) that smaller firms are more responsive to monetary policy through bank credit, but the measure of size that is relevant seems different.

We next turn to firm ownership, which we find to be systematically associated with the level of loan amount in the cross-section (larger for SOEs, smaller for the rest). We do not find evidence of SOEs experiencing disproportionately larger increase in loan amounts. If anything, the domestic private firms and the foreign firms are associated with higher point estimate of the increase in the loan amount. This is more consistent with monetary easing benefiting financially-constrained firms as opposed to systematically-favored firms.

Figure 3.2 provides a graphical comparison between SOEs and private firms complementary to the regression results. Indeed, loan amounts increase significantly following monetary easing announcements, however there are no noticeable differences comparing the responses of SOEs versus private firms. This again suggests that monetary easing does not disproportionately benefit the systematically-favored firms.
Table 3.3: Differential Change in Credit Amount Following Monetary Easing

<table>
<thead>
<tr>
<th>LN(CREDIT AMOUNT)_{it}</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>POST_{t}</td>
<td>0.05**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST_{t} * SOE_{i}</td>
<td>0.20</td>
<td>0.45*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.27)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Collective_{i}</td>
<td>0.22</td>
<td>0.47*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.26)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Private_{i}</td>
<td>0.36*</td>
<td>0.58**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.22)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * HKMacauTaiwan_{i}</td>
<td>0.36*</td>
<td>0.65*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.34)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Foreign_{i}</td>
<td>0.41*</td>
<td>0.65**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.25)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Other_{i}</td>
<td>0.29</td>
<td>0.49**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.21)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(EMPLOYEES_{it})</td>
<td>0.04*</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(REGISTERED CAPITAL_{it})</td>
<td>-0.04***</td>
<td>-0.04***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LISTED FIRM_{it}</td>
<td>-0.03</td>
<td>-0.04</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(DEPOSITS_{it})</td>
<td>0.02**</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * INTERNAL RISK RATING_{it}</td>
<td>-0.02*</td>
<td>-0.02**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
</tbody>
</table>

| Event Fixed Effect | YES | YES | YES |
| Firm Controls | YES | YES |     |
| Firm Controls × Event Fixed Effect | YES |     |     |

| N | 276572 | 276572 | 276572 |
| Adjusted-R^2 | 0.10 | 0.34 | 0.35 |

Note: This table reports regression results for the changes in loan amounts before and after monetary policy events within the -30 days, +30 days window. Columns (1) reports the average changes without controls. Columns (2) reports estimated results for regression equation (3.1). Columns (3) reports estimated results for regression equation (3.3). For each variable the first row lists the coefficient, the second row lists the robust standard error that is corrected for clustering at the year-month and firm level; the corresponding significance levels are adjacent to the coefficient in the second column.
We also note that figure 3.2 does not support the notion of “state advances, private retreats” in bank lending to firms. In fact, new loans to private firms increased faster than new loans to SOEs in this 5-year period, catching up from 75% of new loans to SOEs in January 2012 to virtually equal towards the end of 2016. This suggests that private firms continue to take up larger share of external financing as financial market develops.

### 3.4.2 Changes in Loan Rates following Monetary Policy Events

The next two tables report the results on the differential changes in interest rates on new loans made before and after monetary policy events within the -30 days, +30 days window. Table 3.4 reports the results using the interest rate level on fixed-rate
loans as the dependent variable. Table 3.5 reports the results using the interest rate multiple on adjustable-rate loans as the dependent variable.

It is interesting to note first that we find much smaller changes in the interest rates on new loans before and after monetary easing. Note than the units for the dependent variables in Table 3.4 and Table 3.5 are percentage points. Compared to the average change in the loan amount on the new loans (an average increase of 5%), we find in column (1) of Table 3.4 that there seem to be no decrease in the interest rate on new fixed-rate loans following monetary easing, and there seem to be an average decrease of merely 0.48% in the interest rate multiple on new adjustable-rate loans (which corresponds to a 3 basis points change in the average credit spread). We do note that the interest rate on new adjustable-rate loans would decrease automatically if the monetary easing event involves a lowering of the benchmark interest rates. Overall, the average response in the interest rate on new loans to monetary easing seems to suggest that the interest rate seem to play a minor role in monetary easing in China.

As for our main object of interest, the differential changes across firm characteristics (shown in columns (2) and (3) of Table 3.4 for the interest rate level on fixed-rate loans and columns (2) and (3) of Table 3.5 for the the interest rate multiple on adjustable-rate loans), we find no consistent differential responses in the interest rate on new loans across firm characteristics: No firm characteristics show consistently significant coefficients when interacted with the event dummy POST, and sometimes the point estimates on the interaction terms are of opposite signs for the interest rate level on fixed-rate loans and for the the interest rate multiple on adjustable-rate loans.

We take two suggestive indications from our interest rate results. First, the relationship between the average interest rates and monetary easing seems to be more complex than the simplest scenario under which supply and demand for credit are price elastic, market clears and monetary easing is an outward shift in the credit
Table 3.4: Differential Change in Interest Rates Following Monetary Easing: Fixed-rate Loans

<table>
<thead>
<tr>
<th>Interest rate on FRLs (percentage points)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LOAN RATE</strong>&lt;sub&gt;it&lt;/sub&gt;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * SOE&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.15</td>
<td>-0.01</td>
<td></td>
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<tr>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * Collective&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.07</td>
<td>0.06</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * Private&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.12</td>
<td>-0.01</td>
<td></td>
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<td></td>
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<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * HKMacauTaiwan&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.22</td>
<td>-0.5</td>
<td></td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * Foreign&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.03</td>
<td>0.10</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * Other&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.35</td>
<td>-0.23</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * LN(EMPLOYEES&lt;sub&gt;it&lt;/sub&gt;)</td>
<td>-0.01</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * LN(REGISTERED CAPITAL&lt;sub&gt;it&lt;/sub&gt;)</td>
<td>0.03**</td>
<td>0.02</td>
<td></td>
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<tr>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * LISTED FIRM&lt;sub&gt;it&lt;/sub&gt;</td>
<td>0.08</td>
<td>0.17</td>
<td></td>
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<tr>
<td></td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * LN(DEPOSITS&lt;sub&gt;it&lt;/sub&gt;)</td>
<td>-0.02</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST&lt;sub&gt;t&lt;/sub&gt; * INTERNAL RISK RATING&lt;sub&gt;it&lt;/sub&gt;</td>
<td>-0.01</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Event Fixed Effect                  | YES   | YES   | YES   |
| Firm Controls                      | YES   | YES   |       |
| Firm Controls × Event Fixed Effect |       | YES   |       |
| N                               | 95116 | 95116 | 95116 |
| Adjusted-R<sup>2</sup>           | 0.06  | 0.15  | 0.19  |

*Note:* This table reports regression results for the changes in interest rates for new fixed-rate loans before and after monetary policy events within the -30 days, +30 days window. Columns (1) reports the average changes without controls. Columns (2) reports estimated results for regression equation (3.1). Columns (3) reports estimated results for regression equation (3.3). For each variable the first row lists the coefficient, the second row lists the robust standard error that is corrected for clustering at the year-month and firm level; the corresponding significance levels are adjacent to the coefficient in the second column.
Table 3.5: Differential Change in Interest Rate Multiples Following Monetary Easing: Adjustable-rate Loans

<table>
<thead>
<tr>
<th>Interest rate multiple on ARLs</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>POSTt</td>
<td>-0.48***</td>
<td>0.72</td>
<td>0.85</td>
</tr>
<tr>
<td>POSTt * SOE_i</td>
<td>(0.10)</td>
<td>(1.29)</td>
<td>(1.01)</td>
</tr>
<tr>
<td>POSTt * Collective_i</td>
<td>0.21</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>POSTt * Private_i</td>
<td>(1.30)</td>
<td>(1.03)</td>
<td></td>
</tr>
<tr>
<td>POSTt * HKMacauTaiwan_i</td>
<td>1.14</td>
<td>1.42</td>
<td></td>
</tr>
<tr>
<td>POSTt * Foreign_i</td>
<td>(1.21)</td>
<td>(0.93)</td>
<td></td>
</tr>
<tr>
<td>POSTt * Other_i</td>
<td>0.42</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>POSTt * LN(EMPLOYEES_{it})</td>
<td>1.54</td>
<td>1.27</td>
<td></td>
</tr>
<tr>
<td>POSTt * LN(REGISTERED CAPITAL_{it})</td>
<td>(1.19)</td>
<td>(0.92)</td>
<td></td>
</tr>
<tr>
<td>POSTt * LISTED FIRM_{it}</td>
<td>0.12</td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>POSTt * LN(DEPOSITS_{it})</td>
<td>(0.09)</td>
<td>(0.07)</td>
<td></td>
</tr>
<tr>
<td>POSTt * INTERNAL RISK RATING_{it}</td>
<td>-0.13*</td>
<td>-0.08</td>
<td></td>
</tr>
<tr>
<td>Event Fixed Effect</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>YES</td>
<td>YES</td>
<td></td>
</tr>
<tr>
<td>Firm Controls × Event Fixed Effect</td>
<td>YES</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N: 181456 181456 181456
Adjusted-R^2: 0.15 0.26 0.32

Note: This table reports regression results for the changes in interest rate multiples on new adjustable-rate loans before and after monetary policy events within the -30 days, +30 days window. Columns (1) reports the average changes without controls. Columns (2) reports estimated results for regression equation (3.1). Columns (3) reports estimated results for regression equation (3.3). For each variable the first row lists the coefficient, the second row lists the robust standard error that is corrected for clustering at the year-month and firm level; the corresponding significance levels are adjacent to the coefficient in the second column.
supply. Some possibilities are that the demand for credit is price inelastic, that there is credit rationing, or that monetary easing leads to an outward shift in both the credit supply and the credit demand that balances out the interest rate effects. It would be interesting to know exact which or if it is some combination.

Second, the differential changes in the loan amount following monetary easing across firm characteristics is not associated with corresponding differential changes in the loan rates. This is distinct from the first indication. One potential explanation is that equalization of marginal productivities across firms would actually predict that we might find different changes in the quantity of credit but not in the price of credit.

### 3.4.3 Changes in Loan Maturity following Monetary Policy Events

Next, Table 3.6 reports the results on the differential changes in maturity on new loans made before and after monetary policy events within the -30 days, +30 days window.

We find statistically non-significant effects of monetary easing on the maturity of new loans. The point estimate suggests a change in maturity of one week on average, which is economically small. Across firm types, only riskiness associates with differential changes in loan maturity at a 10-percent confidence level in one of the specifications, with the direction being less risky firms having more increase (or less decrease) in maturity on new loans following monetary easing announcements.

### 3.5 Conclusion

In this paper, we study the way through which monetary easing loosens credit market conditions in China, and whether there are differential changes in quantity, price, and maturity of bank credit across firm types.
Table 3.6: Differential Change in Loan Maturity Following Monetary Easing

<table>
<thead>
<tr>
<th>Maturity (months)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATURITY_{it}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST_{t}</td>
<td>-0.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>POST_{t} * SOE_{i}</td>
<td>-2.56</td>
<td>-3.91</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Collective_{i}</td>
<td>1.97</td>
<td>-0.44</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Private_{i}</td>
<td>0.66</td>
<td>-2.01</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * HKMacauTaiwan_{i}</td>
<td>-0.13</td>
<td>-2.72</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Foreign_{i}</td>
<td>0.19</td>
<td>-2.46</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * Other_{i}</td>
<td>0.76</td>
<td>-1.88</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(EMPLOYEES_{it})</td>
<td>0.19</td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(REGISTERED CAPITAL_{it})</td>
<td>-0.10</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LISTED FIRM_{it}</td>
<td>0.22</td>
<td>-0.56</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * LN(DEPOSITS_{it})</td>
<td>0.04</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>POST_{t} * INTERNAL RISK RATING_{it}</td>
<td>-0.09*</td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>Event Fixed Effect</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>YES</td>
<td>YES</td>
<td></td>
</tr>
<tr>
<td>Firm Controls × Event Fixed Effect</td>
<td>YES</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>220364</td>
<td>220364</td>
<td>220364</td>
</tr>
<tr>
<td>Adjusted-R²</td>
<td>0.01</td>
<td>0.13</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Note: This table reports regression results for the changes in loan maturity on new loans before and after monetary policy events within the -30 days, +30 days window. Columns (1) reports the average changes without controls. Columns (2) reports estimated results for regression equation (3.1). Columns (3) reports estimated results for regression equation (3.3). For each variable the first row lists the coefficient, the second row lists the robust standard error that is corrected for clustering at the year-month and firm level; the corresponding significance levels are adjacent to the coefficient in the second column.
Taken as a whole, the loan size results as opposed to the interest rate and maturity results suggest that monetary policy work through quantities as opposed to prices and loan terms in bank lending in our sample, in sharp contrast to the conventional wisdom on monetary policy in canonical macroeconomic models, which focuses on funding costs and interest rate changes. In this regard, our results are potentially useful for also constructing realistic models of monetary transmission.

Our results suggest that systematically-favored state-owned firms do not benefit disproportionately more, contrary to common perceptions. Our results show that smaller firms (in terms of registered capital) and firms with lower risk ratings do benefit more, and the effect is concentrated in larger increases in the size of new loans, as opposed to lower interest rates or more favorable maturities. Our results are more supportive of the “excess sensitivity” hypothesis of Gertler and Gilchrist (1994) but not the risk-taking channel of monetary policy. This suggests that the nature of the relationship between monetary policy and risk-taking can be complex and context-dependent.

References


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