Credit Supply and Homeownership

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Abstract

The question of what determines home ownership has been extensively researched in the literature. This paper contributes to the literature by studying the effect of banking deregulation on the likelihood of renters becoming homeowners. We find that renters who experienced both inter-state and intra-state banking deregulations are 8.7 percentage points more likely to become homeowners than other renters, all else being equal. In addition, the impact is larger on households with low income and high debt-to-income ratios. Our estimated impacts are larger than those estimated from state-level data, suggesting that the heterogeneous effects among households are important towards home ownership. Our findings are robust to potential sample selection bias and functional misspecifications.

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1 Introduction

For decades, home ownership has been an essential element of the American Dream. U.S. presidents have been promoting home ownership since 1934, when the Federal Housing Administration was created by President Franklin D. Roosevelt to insure mortgages in part so low-income borrowers could qualify. Through the passing years, administrations touted home owning as a way to put middle- and low-income families on a path to social and financial stability by promoting a more involved citizenry. Successive Clinton and Bush administrations unleashed ambitious programs to promote home ownership, especially for low-income households. President Clinton's "National Homeownership Strategy" in 1995 set a goal of allowing millions of families to own homes, in part, by making financing "more available, affordable, and flexible." President George W. Bush famously said in 2002 that "We can put light where there's darkness, and hope where there's despondency in this country. And part of it is working together as a nation to encourage folks to own their own home." And in a 2004 speech he said again that "We're creating... an ownership society in this country, where more Americans than ever will be able to open up their door where they live and say, welcome to my house, welcome to my piece of property."[1]

In June 2017, the S&P Case-Shiller home price index set a new record high, surpassing the previous high from July 2006. If you are a homeowner, you are not only fulfilling the American dream but also enjoying an ongoing boost in wealth from home price appreciation. However, the homeownership rate has been dropping since 2004 when it reached the peak of 69.2%. It is now just 63.5% at the level of the mid-1960s. In other words, home prices keep rising and hitting new records, but fewer homeowners benefit.

The question of what determines home ownership has been extensively researched in the literature. The determinants of home ownership include: demographic and socioeconomic

[1]There are many benefits of owning a home. Research finds that owning a home is an important mechanism for wealth creation (e.g. Herbert, McCue, and Sanchez-Moyano, 2013), and it also brings many social benefits for families, communities, and the country as a whole (e,g. Green and White, 1997; and Glaeser and Sacerdote, 1999). Coulson (2002) provides an excellent review on the social benefits of homeownership and some related issues.

characteristics of households (Eilbott and Binkowski, 1985; and Gyourko and Linneman, 1996), race of the households (Kain and Quigley, 1972; Yinger, 1995; and Munnell et al. 1996), household income and wealth (Gyourko et al. 1999; Charles and Hurst, 2002; and Hilber and Liu, 2008), intergenerational transfers (Guiso and Jappelli, 2002), downpayment (Kiyotaki, Michaelides and Nikolov, 2011), tax-shelter effect (Ebrill and Possen, 1982; Charles and Hurst, 2002), and immigration factor (Coulson, 1999).

We add to this line of research by studying the real effect of banking deregulations on home ownership at the household level. Most states in the U.S. removed restrictions on intra-state branching and inter-state banking during 1980s-1990s. Banking deregulations intensified bank competition and increased credit supply, which likely affected economic performance. Strahan (2003) presents empirical evidence that banking deregulations led to substantial and beneficial real effects on the economy. Many other studies examine how the banking deregulations affect corporate innovation (e.g. Amore, Schneider and Zaldokas, 2013), personal bankruptcy (e.g. Dick and Lehnert, 2010), market structure of non-financial sectors (e.g. Cetorelli and Strahan, 2006), and entrepreneurship (e.g. Black and Strahan, 2002).

In this paper, we study the impact of banking deregulations on the likelihood of households becoming homeowners. In particular, we follow a sample of renters in the Panel Study of Income Dynamics (PSID) data in 1984 and 1989, and separate them into two groups: one group of renters experienced banking deregulations in the next 5 years, while the other group did not. We then analyze the difference in the likelihood of becoming homeowners in the next 5 years between these two groups.[2] We find that after controlling for observables, including household demographic and socio-economic characteristics, state and year fixed effects, and time-varying state-level variables, the effects of increasing credit supply measured

[2]We use the 1984, 1989 and 1994 waves of the survey data, because banking deregulations remained static before 1970s and began to change from 1970s to early 1990s, and completed by 1994 with the passage of Riegle-Neal Interstate Banking and Branching Efficiently Act (IBBEA). Numerous studies also limit their data sample to the mid-1990s, such as Amore, Schneider and Zaldokas (2013); Dick and Lehnert (2010); Cetorelli and Strahan (2006); Black and Strahan (2002); and Kroszner and Strahan (1999).

by both intra-state and inter-state banking deregulations are economically important and statistically significant. In particular, renters who experienced both inter-state and intra-state banking deregulations are 8.7 percentage points more likely to become homeowners than other renters, all else being equal. Given that the unconditional probability of renters becoming homeowners is 26.3 percent, the 8.7 percentage-point increase in the probability is economically important. In other words, banking deregulations, by removing the barriers to branching within state and to out-of-state bank entry, can explain as high as a 33% increase in the likelihood of households becoming homeowners.[3] Our results are robust to potential sample-selection bias and functional misspecifications.

There are several possible explanations no how banking deregulations affect the transition of renters to homeowners. We first look at a possible explanation related to income; banking deregulations may boost household income, especially those in the lower part of the income distribution, making home ownership more affordable for these households. Indeed, we find that banking deregulations have a positive impact on household income, and the impact is larger for households in the lower part of income distribution.

The second possible explanation is related to technology. Dick and Lehnert (2010) suggest that banking deregulations improve financial technology innovation, which further improves lenders' ability to more accurately price for credit risk and therefore offer credit to higher-risk households. If this is the case, the impact of bank deregulation should be larger for higher-risk renters. We indeed find such evidence.

The findings of this paper have important policy implications, especially given a large drop in homeownership rate since the 2007-2009 financial crisis. It suggests that both defaults and the worsening credit market conditions have played important roles in the recent big drop of the homeownership rate. The findings also suggest that government policy aiming to increase credit supply will have a significant effect on improving the homeownership rate. There is an on-going debate whether the Dodd-Frank Act should be dismantled. The

[3] 33% is obtained by calculating the ratio of 8.7 percent to 26.3 percent, i.e., 8.7%/26.3%=33%.

Dodd-Frank Act places major regulations of the financial industry in the hands of the U.S. government during the crisis. Undoubtedly, the Act has greatly improved financial stability after the 2007-2009 financial crisis. With the economy continuing to heal and the U.S. unemployment rate dropping to 4.3% in May 2017–its lowest level since May 2001, to loosen the Dodd-Frank Act will certainly help more households to own their own homes.

The paper closest to this study is Vigdor (2006). Vigdor (2006) examines the impact of credit supply on home price and home ownership, by using another instrument of credit supply–mortgage product innovations. He finds that although recent mortgage innovations increased credit supply to the housing market, they served primarily to increase house prices rather than home ownership. His finding suggests that increasing credit supply may not necessarily increase home ownership. A possible explanation could be that, when credit supply increases, households enjoy easy access to mortgage credits or lower mortgage rates; but they also find that saving is not necessary for rainy days because borrowing money is easy from the bank when they have unexpected cash needs. This leads the households to overspend when credit supply increases. As a result, increasing credit supply does not necessarily result in home ownership increase. In other words, as a prior, it is unclear whether banking deregulations increase home ownership.

The rest of the paper proceeds as follows. In the next section, we describe the nature of the banking deregulations in the United States since 1970s. In Section 3, we describe our data and present some summary statistics. In Section 4, we present our main empirical results on the effect of banking deregulations on the likelihood of renters becoming homeowners. Our findings are robust to potential sample selection bias and functional misspecifications. In Section 5, we study the possible explanations of the effect. Section 6 provides some concluding remarks and discussions.

2 Banking Deregulations

Banking was a highly regulated industry. The geographic expansion of banking has been restricted in U.S. by Mcfadden Act of 1927 and later the Douglas Amendment to the Banking Holding Company Act of 1956. Over the 1970s to early 1990s, U.S. states gradually removed the restrictions on the expansion of banking activities within and across the states. States normally deregulate intra-state banking and then move to deregulate inter-state banking. Intra-state deregulation allows banks to expand within states, and inter-state deregulation allows banks to expand beyond state boundaries. The deregulatory process was completed with passage of the Interstate Banking and Branching Efficiency Act of 1994 (IBBEA). Federal legislation mandated complete inter-state banking as of 1997.

Following Jayaratne and Strahan (1996), we choose the date of deregulation as the date on which a state permitted branching via mergers and acquisitions (M&A) through the holding company. This is the first step in the deregulation process, followed by removing other restrictions. Most banks enter new markets by buying existing banks or branches. Table 1 has the years each state deregulated on intra-state branching and inter-state banking. By 1980, about a third of states have deregulated the intra-state branching; only the state of Maine has removed restrictions on inter-state banking. The deregulation process was completed in 1997 as mandated by the Riegle-Neal Interstate Banking and Branching Efficient ACT of 1994. We have the data for 50 states and the District of Columbia. Consistent with the literature on branching deregulation (e.g., Black and Strahan, 2002; Dick and Lehnert, 2010), we remove Delaware and South Dakota because the structure of their banking systems was heavily affected by laws that made them centers for the credit card industry.

The deregulation of intra-state branching and inter-state banking increases the potential entry of new banks and reduces the market power of incumbents. In fact, for an average state, the fraction of assets held by out-of-state bank holding companies rose from 0% in mid-1970 to 23% in mid-1990 (Kerr and Nanda, 2010). The deregulations of banks have increased banks' efficiency, benefited the real economy and improved the geographic diversification

(Jayaratne and Strahan, 1998; Strahan, 2003; and Goetz, Laeven, and Levine, 2013). In addition, Dick and Lehnert (2010) show that out-of-state banks adopt more sophisticated monitoring and screening technologies than local banks, further reduce the cost of credit supply.

Table 1: Years of Banking Deregulations in Each State

	Year of			Year of	
State	inter-state deregulation	intra-state deregulation	State	inter-state deregulation	intra-state deregulation
AK	1982	1960	MT	1993	1990
AL	1987	1981	NC	1985	1960
AR	1989	1994	ND	1991	1987
AZ	1986	1960	NE	1990	1985
CA	1987	1960	NH	1987	1987
CO	1988	1991	NJ	1986	1977
CT	1983	1980	NM	1989	1991
DC	1985	1960	NV	1985	1960
DE	1988	1960	NY	1982	1976
FL	1985	1988	OH	1985	1979
GA	1985	1983	OK	1987	1988
HI	1995	1986	OR	1986	1985
IA	1991	1999	PA	1986	1982
ID	1985	1960	RI	1984	1960
IL	1986	1988	SC	1986	1960
IN	1986	1989	SD	1988	1960
KS	1992	1987	TN	1985	1985
KY	1984	1990	TX	1987	1988
LA	1987	1988	UT	1984	1981
MA	1983	1984	VA	1985	1978
MD	1985	1960	VT	1988	1970
ME	1980	1975	WA	1987	1985
MI	1986	1987	WI	1987	1990
MN	1986	1993	WV	1988	1987
MO	1986	1990	WY	1987	1988
MS	1988	1986			

3 The PSID Dataset

The Panel Study of Income Dynamics (PSID) dataset is a longitudinal household survey started in 1968 with a sample of over 18,000 individuals living in over 5,000 families in the United States. Individuals in each household were followed annually from 1968 to 1997, and biannually after 1997. The PSID data set is unique for the current study in several respects. First, the data set contains detailed household demographic information (i.e., age, gender, race, marital status and geographic location) and socioeconomic characteristics (i.e., education, employment status, income, and wealth). Second, each household is assigned a unique identification number, by which we can follow each household over time. Finally, the data set is nationally representative.

We use the 1984, 1989 and 1994 waves of the survey data, because banking deregulations remained static before 1970s and began to change from 1970s to early 1990s with the passage of IBBEA in 1994. The household wealth information is only available in 1984, 1989 and 1994 and then biannually since 1999. We focus on a sample of renters in 1984 and 1989. We drop the renters who moved across states during the sample period, to eliminate the impact from the change of states. We also omit observations with missing values.

The final data contain 4,060 renters in 1984 and 1989. We classify these renters into two groups: one group of renters experienced banking deregulations in the next 5 years, while the other group did not. We then analyze the difference in the likelihood of becoming home owners in the next 5 years between these two groups of renters.

Table 2 provides summary statistics for the these groups of renters, and for renters who become home owners in the next 5 years. The variables shown in Table 2 include household demographic and socioeconomic characteristics from the PSID, and three time-varying state-level variables from other data sources: the median house price is from the Federal Housing Finance Agency, the median household income from the Federal Reserve Bank of St. Louis, and the unemployment rate from the Bureau of Labor Statistics. Al these variables are used as covariates in our estimations.

Table 2: Summary Statistics

	Intra-state deregulations		Inter-state deregulations		Become homeowners in next 5 years	
	No	Yes	No	Yes	No	Yes
Share of renters becoming homeowners in next 5 years	26.3%	32.5%	27.0%	28.4%	N/A	N/A
Household characteristics						
Age	40.40	39.59	40.66	39.57	42.12	35.31
Race						
White	0.75	0.75	0.76	0.73	0.71	0.85
Black	0.23	0.23	0.22	0.23	0.27	0.13
Other	0.02	0.02	0.02	0.04	0.03	0.02
Female	0.43	0.42	0.42	0.44	0.51	0.21
Married	0.28	0.29	0.27	0.30	0.22	0.44
Children	0.62	0.65	0.58	0.70	0.61	0.66
Education (yrs)	12.28	11.92	12.42	11.88	11.94	12.94
Health						
Very good	0.23	0.24	0.23	0.24	0.20	0.32
Good	0.31	0.30	0.32	0.29	0.29	0.37
Fair	0.27	0.24	0.25	0.28	0.28	0.23
Bad	0.14	0.16	0.15	0.13	0.17	0.06
Very bad	0.05	0.05	0.05	0.07	0.07	0.02
Unemployed	0.06	0.08	0.05	0.08	0.08	0.03
Family income ($1,000)	21.67	16.70	22.62	17.59	18.27	27.12
Wealth (excluding home, $1,000)	21.51	15.65	23.01	16.07	19.18	23.49
Time-varying state variables						
Median house price ($1,000)	83.68	60.67	88.27	64.43	80.41	76.04
Median hhld income ($1,000)	26.95	22.91	28.31	22.65	26.24	25.96
Unemployment rate (%)	6.03	7.72	5.51	7.75	6.36	6.35
Number of observations	3,224	836	2,212	1,848	3,039	1,021

Note: data is weighted using PSID core sample weights. All variables are from the PSID except the time-vary state-level variables: the median house price is from the Federal Housing Finance Agency, the median household income from the Federal Reserve Bank of St. Louis, and the unemployment rate from the Bureau of Labor Statistics.

The preliminary results from Table 2 reveal two interesting observations that motivate us to examine the issues further. First, we find that, unconditionally, renters residing in the states that experienced either intra- or inter-state deregulation are more likely to become home owners in the next five years. However, they tend to be unemployed and have low family income, low wealth and low education level. Second, renters who become home owners in the next five years tend to be employed, be healthy, have high income and wealth, and reside in states with lower median house prices. The systematic differences in these observables highlight the importance of controls in the analysis we conduct.

4 Main Empirical Findings

We use the pooled logit model to study the impact of bank deregulations on the likelihood of households becoming homeowners. The results, however, are robust to various estimation methods, as we will show later. The structure of the pooled logit model has the latent variable format:

$$Transfer^*_{i,t} = \alpha\, Intra_{s,t} + \beta\, Inter_{s,t} + \gamma'\, X_{i,t} + \epsilon_{i,t}, \tag{1}$$

$$Transfer_{i,t} = \begin{cases} 1, & \text{if } Transfer^*_{i,t} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The first equation is the latent variable equation, where $Transfer^*_{i,t}$ is a latent variable that can be written as a linear function of the regressors. The second equation is the choice equation, where $Transfer_{i,t}$ is an indicator variable of renters transferring to home owners, which equals 1 if Renter i in Year t becomes a home owner in the next 5 years, and zero otherwise. $Intra_{s,t}$ is the indicator variable of intra-state deregulation, which equals 1 if the State s where Renter i lives in Year t experiences intra-state deregulation in the next 5 years, and 0 otherwise. Similarly, $Inter_{s,t}$ is the indicator variable of inter-state deregulation, which equals 1 if the State s where Renter i lives in Year t experiences inter-state deregulation in the next 5 years, and 0 otherwise. $X_{i,t}$ is a vector of other regressors, including household demographic and socio-economic characteristics, state and year fixed effects, and time-varying state-level variables. $\epsilon_{i,t}$ is the error term.

We estimate a series of different specifications by gradually increasing the number of controlled variables in $X_{i,t}$ to see their effects on the probability of renters becoming home-owners. The estimated coefficients, standard errors, marginal effects and significance levels are reported in Table 3.

We begin with the simplest specification by controlling for $Intra_{s,t}$ and $Inter_{s,t}$ only. The results are reported in Column 1 of Table 3. The marginal effect indicates that, without controlling for any observables, renters in the states that experienced intra-state deregulation on average are 5.9 percentage points more likely to become homeowners, and the difference is statistically significant at the 1% level. For inter-state deregulation, the effect is economically negligible (0.1 percentage point) and statistically insignificant at the 10% level.

As a first step toward measuring the effect of banking deregulations on home ownership, in Specification 2 we control for the state and year fixed effects and the time-varying state-level variables including logged median house price, logged median household income and state unemployment rate. All the covariates in this specification are state-level variables. The results, reported in Column 2 of Table 3, show that the likelihood of households becoming home owners increases by 3.3 percentage points after the intra-state banking deregulation and by 4.6 percentage points after the inter-state banking deregulation. More importantly, the effects of both intra-state and inter-state deregulations are statistically significant.

Table 3: The Impact of Banking Deregulations on the Probability of Renters Becoming Home Owners
(Pooled logit regressions)

	(1)			(2)			(3)		
	Marg. effect	Coef.	Sig. level	Marg. effect	Coef.	Sig. level	Marg. effect	Coef.	Sig. level
Intra-state deregulation	0.059	0.298	***	0.033	0.170	**	0.030	0.187	**
		(0.103)			(0.074)			(0.095)	
Inter-state deregulation	0.001	0.003		0.046	0.235	***	0.057	0.354	***
		(0.101)			(0.037)			(0.040)	
Time-varying state variables									
Log(median house price)				-0.218	-1.112	***	-0.148	-0.920	***
					(0.271)			(0.255)	
Log(median hhld income)				0.248	1.270	**	0.056	0.350	
					(0.580)			(0.636)	
Unemployment_rate (%)				-0.008	-0.039		-0.012	-0.075	
					(0.046)			(0.050)	
Household characteristics									
Age							0.007	0.046	**
								(0.023)	
Age squared ($\times 10^4$)							-1.050	-6.522	***
								(2.420)	
Race (white omitted)									
Black							-0.085	-0.528	**
								(0.217)	
Other							-0.086	-0.533	*
								(0.297)	
Female							-0.102	-0.633	***
								(0.148)	
Married							0.061	0.378	***
								(0.107)	
# of children							0.018	0.113	**
								(0.045)	
Change in # of children							0.065	0.404	***
								(0.046)	
Education (less than high school omitted)									
High school degree							0.024	0.152	
								(0.108)	
College degree							0.060	0.373	***
								(0.096)	
Health status (very bad omitted)									
Good							-0.026	-0.164	*
								(0.097)	
Fair							-0.051	-0.315	***
								(0.058)	
Bad							-0.116	-0.721	***
								(0.202)	
Very bad							-0.093	-0.575	
								(0.416)	

Continued on next page

Table 3: – *Continued from previous page*

	(1)			(2)			(3)		
	Marg. effect	Coef.	Sig. level	Marg. effect	Coef.	Sig. level	Marg. effect	Coef.	Sig. level
Unemployed							-0.110	-0.686	**
								(0.285)	
Log(family income)							0.031	0.193	***
								(0.055)	
Quartile of wealth									
(1st quartile omitted)									
2nd quartile							0.029	0.183	
								(0.134)	
3rd quartile							0.114	0.706	***
								(0.194)	
4th quartile							0.103	0.637	
								(0.438)	
State and year fixed effects		No			Yes			Yes	
Log likelihood		-35,990			-35,466			-29,915	
Number of observations		4,060			4,060			4,060	

Note: All regressions are weighted using PSID core sample weights. All standard errors are clustered at the state level. All covariates are from the PSID except the time-vary state-level variables: median house price is from the Federal Housing Finance Agency, median household income from the Federal Reserve Bank of St. Louis, and unemployment rate from the Bureau of Labor Statistics. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

In Specification 3, we further control for household demographic and socioeconomic variables including age, gender, race, marital status, education, number of children, change in the number of children, employment status, income and wealth. In addition, we have learned from Table 2 that renters who become home owners in the next five years tend to be healthier, so we also control for renter's health status in Specification 3.[4] The results, reported in Column 3 of Table 3, show that renters are 3.0 (5.7) percentage points more likely to become home owners after their residing states experienced the intra-state (inter-state) banking deregulation, and the impact is statistically significant at the 5% (1%) level.

The results from Table 3 have two important implications. First, a comparison between Columns 2 and 3 suggests that the heterogeneous effects among households are important

[4]Initially we also control for marginal tax rate in Specification 3, but it turns out to be statistically insignificant. Charles and Hurst (2002) have a similar finding: marginal tax rate is significant when only controlling for race, age, education, marital status, and number of children. However, it becomes statistically insignificant after controlling for income, wealth and employment status.

towards home ownership. In other words, estimations using state-level data are potentially biased: the impact of intra-state deregulation is overestimated in the state-level data, while the impact of inter-state deregulation is underestimated. Second, renters who live in the states which experienced both inter-state and intra-state banking deregulations are 8.7 percentage points more likely to become home owners (5.7 percentage points from the inter-state deregulation and 3.0 percentage points from the intra-state deregulation). Given that the unconditional probability of renters becoming owners is about 26.5 percent, the 8.7 percentage-point increase represents a 33% increase in the likelihood of households becoming home owners.[5]

The results on the other covariates are also sensible in Table 3. For instance, holding everything else constant, a 1% increase in the state median house price decreases the likelihood of households becoming home owners by 0.15 percentage point. All else being equal, female renters are 10.2% less likely to become home owners than male renters, and married renters are 6.1% more likely to become home owners than other renters. The transition rate from renters to home owners increases with the family size (i.e., the number of children), the educational level and the family income, ceteris paribus.

4.1 Endogeneity of Banking Deregulation

Kroszner and Strahan (1999) argue that banking deregulation is an endogenous decision affected by many state-level factors. For example, deregulation may occur earlier in states (i) with fewer small banks, (ii) where small banks were financially weak, and (iii) with more small and bank-dependent firms. To the extent that the state-level unobservables affect states' decisions on banking deregulations and renters' decisions to become homeowners, our estimation may be biased because of the endogeneity of banking deregulation. However, our results are unlikely to be affected by this potential endogeneity, for the following three reasons: First, since we have controlled for the state fixed effects, we are comparing the

[5]33%=8.7%/26.5%.

probability of a renter becoming a home owner before and after her/his residing state experienced banking deregulation, instead of a cross-sectional comparison between states. All of the impact from cross-sectional variation should be removed by the state fixed effects. That is, any persistent differences across states (such as the number of small banks and the financial conditions of small banks) are unlikely to affect our results.

Second, the state fixed effects may not be sufficient to fully address the issue, as some factors that cause states to endogenously deregulate their banking sector may be time-varying. To mitigate this concern, we have also controlled for time-varying state characteristics, such as employment, median house price and median household income, and our results are robust to the inclusion of these controls.

Third, while we have controlled for a detailed set of factors in the estimations, it is possible that a small amount of selection on unobservables could explain much of the estimated effect of banking deregulations. We now explore this possibility by using the relationship between banking deregulations and the observables to make inferences about the relationship between selection on the observables and selection on the unobservables.

We take the approach in Altonji et al. (2005, 2008). This technique estimates the relative amount of selection on unobservables required to explain the estimated effects of banking deregulations if the true effects are zero (i.e., the null hypothesis). We apply this technique for intra- and inter-state banking deregulation separately. In the following explanation of this technology, we will focus on intra-state banking deregulation.

The technique relies on the following condition:

$$\frac{E(\epsilon|Intra=1)-E(\epsilon|Intra=0)}{Var(\epsilon)}=\frac{E(\gamma'X|Intra=1)-E(\gamma'X|Intra=0)}{Var(\gamma'X)}, \tag{3}$$

where ϵ is the error term from (1), and is an index of unobservables that affect households' decisions to become home owners. Similarly, $\gamma'X$ is the index of observables in (1) that affect household's decisions to become home owners.

The left-hand side of (3) is the relationship between *Intra* and the mean of ϵ, and represents selection (into intra-state banking deregulation) that relies on the unobservables (Altonji et al., 2002). Similarly, the right-hand side of (3) is the relationship between *Intra* and the mean of $\gamma' X$, and represents selection on observables. Therefore, (3) is equivalent to saying that, for intra-state banking deregulation, selection on unobservables is the same as selection on observables. Note that all items in (3) can be estimated from the data, except for $E(\epsilon|Intra = 1) - E(\epsilon|Intra = 0)$. In perticular, under the null hypothesis of no intra-state banking-deregulation effect, we can consistently estimate γ and thus $\gamma' X$, from a regression of Equation (1) with the constrain that $\alpha = 0$.

Let $\widetilde{Intra}$ be the residual of a regression of *Intra* on X so that $Intra = \mu' X + \widetilde{Intra}$. Then substituting this equation into (1), one gets

$$Transfer^* = \alpha\,\widetilde{Intra} + (\alpha\mu' + \gamma')\,X + \beta\,Inter + \epsilon. \tag{4}$$

Given that $\widetilde{Intra}$ is orthogonal to X, (4) leads to

$$\begin{aligned} plim(\tilde{\alpha}) &= \alpha + \frac{Cov(\widetilde{Intra}, \epsilon)}{Var(\widetilde{Intra})} = \alpha + \frac{Cov(Intra - \mu' X, \epsilon)}{Var(\widetilde{Intra})} = \alpha + \frac{Cov(Intra, \epsilon)}{Var(\widetilde{Intra})} \\ &= \alpha + \frac{Var(Intra)}{Var(\widetilde{Intra})} * [E(\epsilon|Intra = 1) - E(\epsilon|Intra = 0)]. \end{aligned} \tag{5}$$

That is, if selection on unobservables is the same as selection on observables, then the bias in the estimated intra-state banking deregulation impact due to selection on unobservables is:

$$Bias(\alpha) = \frac{Var(Intra)}{Var(\widetilde{Intra})} * [E(\epsilon|Intra = 1) - E(\epsilon|Intra = 0)]. \tag{6}$$

The two items in the fraction of (6), $Var(Intra)$ and $Var(\widetilde{Intra})$, can be estimated directly from the data, and the second item can be calculated from (3). The top section of Table 4 reports these calculation results. In particular, $Bias(\beta)$ is calculated to be 0.133 (Column 5, Table 4). Recall that the estimated coefficient of intra-state banking deregulation is 0.187 (Column 3, Table 3 or Column 6, Table 4). This suggests that the selection on unobservables needs to be about 1.4 times of the selection on observables, which is very unlikely given that we have a detailed list of observables.[6] Therefore, we reject the null hypothesis that the intra-state banking deregulation effect is zero.

The corresponding results for inter-state banking deregulation are reported in the lower part of Table 4. The bias is calculated to be 0.041 (Column 5, Table 4). Given that the the estimated coefficient of intra-state banking deregulation is 0.354 (Column 3, Table 3 or Column 6, Table 4). This suggests that the selection on unobservables needs to be about 8.7 times of the selection on observables, which again is very unlikely. Therefore, we reject the null hypothesis of a zero impact of inter-state banking deregulation.

Table 4: Amount of Selection on Unobservables Relative to Selection on Observables Required to Attribute the Entire Effects of Banking Deregulations to Selection Bias

(1)	(2)	(3)	(4)	(5)
$E(\epsilon \vert Intra=1)-$ $E(\epsilon \vert Intra=0)$	$Var(Intra)/$ $Var(\widetilde{Intra})$	$Bias(\alpha)$	$\hat{\alpha}$	$\hat{\alpha}/$ $Bias(\alpha)$
Intra-State Banking Deregulation				
0.092	1.440	0.133	0.187	1.414
Inter-State Banking Deregulation				
0.011	3.741	0.041	0.354	8.668

4.2 Unobservable Household Characteristics–the Random Effect and Fixed Effect Logit Models

Given that the PSID is longitudinal data, more empirical tools are available that can improve the efficiency of our estimation of the impact of banking deregulations. For example, one concern of the pooled logit model is that the latent variable equation (1) may be

$$Transfer^*_{i,t} = \alpha\, Intra_{s,t} + \beta\, Inter_{s,t} + \gamma'\, X_{i,t} + U_i + \epsilon_{i,t}, \tag{7}$$

[6] 0.187/0.133≈1.4.

where U_i includes all unobservable household characteristics that are constant over time, such as risk aversion of the household. If this is the case, our previous results from the pooled logit regressions may be inefficient or biased (due to unobservables). To mitigate this concern, we use both the random effect and the fixed effect models to re-estimate the coefficients. In theory, if U_i is uncorrelated with $\epsilon_{i,t}$, both the random effect and the fixed effect models are consistent, but the random effect model is more efficient. On the other hand, if U_i is correlated with $\epsilon_{i,t}$, then only the fixed effect model is consistent.

After accounting for unobserved heterogeneity of households, key results from the random effect and the fixed effect logit estimations are reported in Table 5. Consistent with our pooled logit regression, inter-state banking deregulation has a larger impact than intra-state deregulation on the transition probability from renters to homeowners: the transition rate increases by 3.6 to 4.7 percentage points after intra-state deregulation (compared to 3.0 percentage points from the pooled logit model), and by 4.3 to 6.2 percentage points after inter-state deregulation (compared to 5.7 percentage points from the pooled logit model). The other covariates in the random effect and the fixed effect logit estimations are the same as in Column 3 of Table 3; that is, we have controlled for household demographic and socioeconomic characteristics, time-varying state-level variables, and year and state fixed effects. In sum, the random effect and fixed effect estimations reaffirm our main results.

4.3 Sample Selection Bias–the Heckman Copula Model

The outcome variable–whether a household becomes a home owner–is only observable for renters. If the subsample of renters is not a random sample of the entire population of American households, our previous estimators are likely to suffer from sample selection bias. Indeed, in our data, renters tend to be young, single, unemployed, and have lower income, lower wealth and worse health conditions (see Table 6).

To correct this potential bias, we implement the *Heckman copula model* (Smith, 2003; and Hasebe, 2013), which uses the full sample of households, including both renters and

Table 5: Impact of Bank Deregulations on Probability of Renters Becoming Home Owners
(Random effect and fixed effect logit regressions)

	(1) Random effect			(2) Fixed effect		
	Marginal effect	Coef.	Sig. level	Marginal effect	Coef.	Sig. level
Intra-state deregulation	0.047	0.374	***	0.036	0.355	***
		(0.046)			(0.039)	
Inter-state deregulation	0.062	0.490	***	0.043	0.422	***
		(0.054)			(0.031)	
Other controls:						
Household characteristics		Yes			Yes	
Time-varying state variables		Yes			Yes	
Year and state fixed effects		Yes			Yes	
Log likelihood		-28,853.1			-4,851.41	
Number of observations		4,060			4,060	

home owners. The model consists of two equations: a selection equation and an outcome equation. The selection equation is

$$Renter_{i,t} = \begin{cases} 1, & \text{if } Renter^*_{i,t} = \lambda' \tilde{X}_{i,t} + \xi_{i,t} > 0, \\ 0, & \text{if } Renter^*_{i,t} = \lambda' \tilde{X}_{i,t} + \xi_{i,t} \leq 0, \end{cases} \tag{8}$$

where $Renter_{i,t}$ is the indicator variable of renters. $Renter^*_{i,t}$ is the corresponding latent variable. $\tilde{X}_{i,t}$ is a vector of covariates, including $Intra_{s,t}$, $Inter_{s,t}$ and $X_{i,t}$ from (1). $\xi_{i,t}$ is the error term that follows a logistic distribution.

The outcome of interest is the indicator of renters becoming home owners $Transfer_{i,t}$, which is observable only when $Renter_{i,t} = 1$. To gauge the role of selection bias in a simple way, we ignore the fact that $Transfer_{i,t}$ is estimated by a logit model and treat $Transfer_{i,t}$ as though it is estimated by a linear probability model as follows:

$$Transfer_{i,t} = \begin{cases} \alpha Intra_{s,t} + \beta\, Inter_{s,t} + \gamma'\, X_{i,t} + \epsilon_{i,t} & \text{, if } Renter_{i,t} = 1, \\ . & \text{, if } Renter_{i,t} = 0. \end{cases} \tag{9}$$

Table 6: Comparative Statistics for Renters and Home Owners

	Renters	Homeowners
Household characteristics		
Age	40.24	50.42
Race		
White	0.75	0.90
Black	0.23	0.08
Other	0.02	0.02
Female	0.42	0.19
Married	0.28	0.74
Children	0.62	0.73
Education	12.21	12.71
Health status		
Very good	0.23	0.24
Good	0.31	0.34
Fair	0.26	0.27
Bad	0.14	0.12
Very bad	0.05	0.03
Unemployed	0.06	0.02
Family income ($1,000)	20.70	42.06
Wealth (excluding home, $1,000)	20.37	193.72
Time-varying state variables:		
Median house price ($1,000)	79.20	76.45
Median household income ($1,000)	26.16	25.96
Unemployment rate (%)	6.36	6.39
Number of observations	4,060	5,270

Note: data is weighted using PSID core sample weights. All variables are from the PSID except the time-vary state-level variables: the median house price is from the Federal Housing Finance Agency, the median household income from the Federal Reserve Bank of St. Louis, and the unemployment rate from the Bureau of Labor Statistics.

Equations (8) and (9) are called the *Heckman selection model*, which is estimated by the maximum likelihood method. Let f_ξ and f_ϵ be the univariate probability density function (p.d.f.) of $\xi_{i,t}$ and $\epsilon_{i,t}$, respectively, and F_ξ and F_ϵ be the univariate cumulative distribution function (c.d.f.). Similarly, let $f_{\xi,\epsilon}$ be the joint p.d.f. of $\xi_{i,t}$ and $\epsilon_{i,t}$, and let $F_{\xi,\epsilon}$ be the corresponding joint c.d.f.

Then the likelihood of the Heckman selection model is

$$\begin{aligned} L &= \prod_{i=1}^{N}\prod_{t=1}^{T}\left\{\int_{-\infty}^{-\lambda'\tilde{X}_{i,t}} f_\xi(\xi)d\xi\right\}^{Owner_{i,t}} \left\{\int_{-\lambda'\tilde{X}_{i,t}}^{\infty} f_{\xi,\epsilon}(\xi,\epsilon_{i,t})d\xi\right\}^{Renter_{i,t}} \\ &= \prod_{i=1}^{N}\prod_{t=1}^{T}\left\{F_\xi\left(-\lambda'\tilde{X}_{i,t}\right)\right\}^{Owner_{i,t}} \left\{\frac{\partial\left\{F_\epsilon(\epsilon) - F_{\xi,\epsilon}(-\lambda'\tilde{X}_{i,t},\epsilon)\right\}|_{\epsilon=\epsilon_{i,t}}}{\partial\epsilon}\right\}^{Renter_{i,t}} \\ &= \prod_{i=1}^{N}\prod_{t=1}^{T}\left\{F_\xi\left(-\lambda'\tilde{X}_{i,t}\right)\right\}^{Owner_{i,t}} \left\{f_\epsilon(\epsilon_{i,t}) - \frac{\partial F_{\xi,\epsilon}(-\lambda'\tilde{X}_{i,t},\epsilon_{i,t})}{\partial\epsilon_{i,t}}\right\}^{Renter_{i,t}}, \end{aligned} \tag{10}$$

where $Owner_{i,t} = 1 - Renter_{i,t}$ is the home owner indicator variable. To implement the maximum likelihood estimation, we need to make assumptions on the marginal and joint distributions of $\xi_{i,t}$ and $\epsilon_{i,t}$. Following Smith (2003) and Trivedi and Zimmer (2005), we take the copula approach in making the assumptions. A copula is the joint distribution of random variables u_1 and u_2, each of which is marginally uniformly distributed on $[0,1]$. The Sklar's Theorem says that given any two random variables ω_1 and ω_2 with marginal distributions $u_i = F_i(\omega_i), (i = 1,2)$ and joint distribution $F(\omega_1,\omega_2)$, there exists a copula function $C(\cdot)$ such that

$$F(\omega_1,\omega_2) = C(F_1(\omega_1),F_2(\omega_2);\rho) = C(u_1,u_2;\rho), \tag{11}$$

where ρ is a parameter measuring the dependence between ω_1 and ω_2. From (11), one gets

$$\frac{\partial F(\omega_1,\omega_2)}{\partial\omega_1} = \frac{\partial C(u_1,u_2;\rho)}{\partial u_1} \times \frac{\partial F_1(\omega_1)}{\partial\omega_1} = \frac{\partial C(u_1,u_2;\rho)}{\partial u_1} f_1(\omega_1). \tag{12}$$

Applies (12) towards (10), the likelihood function becomes

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T}\left\{F_{\xi}\left(-\lambda'\tilde{X}_{i,t}\right)\right\}^{Owner_{i,t}}\left\{f_{\epsilon}(\epsilon_{i,t}) - \frac{\partial C(u_{\epsilon,i,t}, u_{\xi,i,t};\rho)}{\partial u_{\epsilon}} f_{\epsilon}(\epsilon_{i,t})\right\}^{Renter_{i,t}}, \qquad (13)$$

where $u_{\epsilon,i,t} = F_{\epsilon}(\epsilon_{i,t})$ and $u_{\xi,i,t} = F_{\xi}(\xi_{i,t})$ are the c.d.f. of $\epsilon_{i,t}$ and $\xi_{i,t}$.

There are various copula functions (see Hasebe, 2013), and in this paper, we focus on the Joe copulas function as follows:

$$C(u_1, u_2; \rho) = 1 - [(1-u_1)^{\rho} + (1-u_2)^{\rho} - (1-u_1)^{\rho}(1-u_2)^{\rho}]^{1/\rho}. \qquad (14)$$

Table 7 reports the maximum likelihood estimation of the Heckman copula model with the Joe copula. As shown in Table 7, our main results are robust to the potential sample selection bias: the estimated marginal impact of the intra-state banking deregulation on the transition rate to home ownership is 2.7% (compared to 3.0% in Column 3 of Table 3), and the marginal impact of the inter-state banking deregulation is 4.9% (compared to 5.7% in Column 3 of Table 3). Table 7 also reports a coefficient τ, which ranges between -1 and 1: A value of τ closer to 1 (-1) means a stronger (negative) dependence between the error terms in the selection and the outcome equations, and therefore stronger evidence of sample selection. Table 7 shows evidence of sample selection: τ is -0.115 and significant at the 1% level. The sample selection, however, does not affects our main results. Note that our main results are also robust to the use of other copula functions.

4.4 The Probit Models

So far, we have assumed that the error term, $\epsilon_{i,t}$, in the latent variable (or outcome) equation follows a logistic distribution. If $\epsilon_{i,t}$ instead follows a normal distribution, the model becomes a probit model, and the most efficient estimation method is the probit estimation, the results of which are reported in Columns 1 to 3 of Table 8.

Table 7: Impact of Bank Deregulations on the Probability of Renters Becoming Home Owners
(Heckman copula regression with the Joe copula to control for sample selection bias)

	Coef.	Sig. level		Coef.	Sig. level
Key regressors					
Intra-state deregulation	0.027	***			
	(0.005)				
Inter-state deregulation	0.049	***			
	(0.006)				
Time-varying state variables					
Log(median house price)	-0.153	***	Log(median hhld income)	0.094	
	(0.044)			(0.103)	
Unemployment_rate (%)	-0.012				
	(0.008)				
Household characteristics					
Age	-0.001		Health status (very good omitted)		
	(0.004)		Good	-0.035	*
Age squared	0.000			0.019	
	(0.000)		Fair	-0.062	***
Race (white omitted)				(0.012)	
Black	-0.057	**	Bad	-0.075	***
	(0.025)			(0.025)	
Other	-0.104	***	Very bad	-0.039	
	(0.035)			(0.028)	
Female	-0.077	***	Unemployed	-0.083	***
	(0.018)			(0.018)	
Married	0.046	**	Log(family income)	0.021	***
	(0.021)			(0.004)	
# of children	0.022	***	Quartile of wealth		
	(0.006)		(1st quartile omitted)		
Change in # of children	0.088	***	2nd quartile	0.007	
	(0.009)			(0.019)	
Education			3rd quartile	0.086	***
(less than high school omitted)				(0.024)	
High school degree	0.004		4th quartile	0.034	
	(0.011)			(0.059)	
College degree	0.047	***	τ	-0.115	***
	(0.014)			(0.001)	
Year and state fixed effects			Yes		
Log likelihood			-106,100		
Number of observations			9,330		

Note: This table reports the maximum likelihood estimation results of a Heckman copula model with the Joe copula. The regression is weighted using PSID core sample weights. All standard errors are clustered at the state level. All covariates are from the PSID except the time-vary state-level variables: median house price is from the Federal Housing Finance Agency, median household income from the Federal Reserve Bank of St. Louis, and unemployment rate from the Bureau of Labor Statistics. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level. The coefficient of τ measures the dependence between the error terms in the selection and the outcome equations. Our main results are robust to the use of other copula functions.

Column 1 of Table 8 reports the results from the *pooled probit regression*, where the latent variable equation is same as (1), except that the error term $\epsilon_{i,t}$ follows a normal distribution. Column 2 reports the results from the *random effect probit regression*, where the latent variable equation is same as (7), with $\epsilon_{i,t}$ being normally distributed.

Column 3 reports the results from the *Heckman probit model* to control for the potential sample selection bias. The Heckman probit model is a special case of the Heckman copula model where the error terms in the selection and the outcome equations follow a joint standard normal distribution. More specifically, the model consists of two equations: a selection equation and an outcome equation. The selection equation is the same as (8) and the outcome equation is the same as (1) and (2), except that the error terms $\xi_{i,t}$ and $\epsilon_{i,t}$ now follow a joint standard normal distribution as follows:

$$\begin{pmatrix} \xi_{i,t} \\ \epsilon_{i,t} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right], \tag{15}$$

where ρ is the correlation coefficient.

The Heckman probit model–composed of (1), (2), (8) and (15)–is estimated using the maximum likelihood method. In particular, there are three types of observations in our sample, with the following probabilities:

$$\begin{aligned}
&Prob(Renter_{i,t} = 0) = \Phi(-\lambda' \tilde{X}_{i,t}), \\
&Prob(Renter_{i,t} = 1,\ Transfer_{i,t} = 1) = \Phi_2(\lambda' \tilde{X}_{i,t}, \gamma' \tilde{X}_{i,t}, \rho), \\
&Prob(Renter_{i,t} = 1,\ Transfer_{i,t} = 0) = \Phi(\lambda' \tilde{X}_{i,t}) - \Phi_2(\lambda' \tilde{X}_{i,t}, \gamma' \tilde{X}_{i,t}, \rho),
\end{aligned}$$

where Φ is the standard normal c.d.f. and Φ_2 is the bivariate standard normal c.d.f. The maximum-likelihood method finds values of λ, γ and ρ to maximize the following joint-likelihood function:

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T}\left\{\Phi(-\lambda'\tilde{X}_{i,t})\right\}^{Owner_{i,t}} \times \left\{\Phi_2(\lambda'\tilde{X}_{i,t}, \gamma'\tilde{X}_{i,t}, \rho)\right\}^{Renter_{i,t}\cdot Transfer_{i,t}} \times \left\{\Phi(\lambda'\tilde{X}_{i,t}) - \Phi_2(\lambda'\tilde{X}_{i,t}, \gamma'\tilde{X}_{i,t}, \rho)\right\}^{Renter_{i,t}\cdot(1-Transfer_{i,t})}. \quad (16)$$

In Columns 1 to 3 of Table 8, the controls are the same as in Column 3 of Table 3. Again, results from the various probit regressions suggest that both the intra- and inter-state bank deregulations have positive impacts on home ownership: controlling for observables, the likelihood of households becoming home owners increases by 2.9 to 4.8 percentage points after intra-state deregulation, and by 5.9 to 6.7 percentage points after inter-state deregulation. Both effects are statistically significant at the 1% level. In addition, similar to the results from the Heckman copula model, the estimated ρ in the Heckman probit model is -0.676 and significant at the 1% level, indicating that there is evidence of sample selection, but our main results are robust to the sample selection.

Table 8: Impact of Bank Deregulations on the Probability of Renters Becoming Home Owners (Probit regressions and Propensity Score Matching Method)

	(1) Pooled Probit			(2) Random effect Probit			(3) Heckman Probit			(4) PSM	
	Marg. eff.	Coef.	Sig. level	Marg. eff.	Coef.	Sig. level	Marg. eff.	Coef.	Sig. level	Marg. eff.	Sig. level
Intra-state deregulation	0.029	0.104	**	0.048	0.222	***	0.031	0.086	***	0.023	***
		(0.049)			(0.027)			(0.015)		(0.003)	
Inter-state deregulation	0.059	0.214	***	0.062	0.291	***	0.067	0.186	***	0.049	***
		(0.022)			(0.032)			(0.018)		(0.002)	
ρ								-0.676	***		
								(0.037)			
Other controls:											
State and year fixed eff.		Yes			Yes			Yes		Yes	
Time-varying state var.		Yes			Yes			Yes		Yes	
Hhld characteristics		Yes			Yes			Yes		Yes	
Log likelihood		-29,979			-28,869			-100,824		N/A	
Number of observations		4,060			4,060			9,330		4,060	

Note: The first three columns reports estimates from various probit model regressions. All regressions are weighted using PSID core sample weights. All standard errors are clustered at the state level. All covariates are from the PSID except the time-vary state-level variables: median house price is from the Federal Housing Finance Agency, median household income from the Federal Reserve Bank of St. Louis, and unemployment rate from the Bureau of Labor Statistics. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level. The coefficient of ρ measures the dependence between the error terms in the selection and the outcome equations.

4.5 The Propensity Score Matching (PSM) Model

Equation (1) in both the logit and the probit models assumes linear impacts of covariates on the latent variable. If this assumption is invalid, our previous estimators may be biased due to functional misspecification. To deal with this potential issue, we apply the matching method, more specifically the *propensity score matching (PSM) method*.

The matching estimation is obtained by simply comparing the transition rate (to homeowners) of renters who live in states that experienced banking deregulations versus the transition rate of the other renters who do not. Using terminology from the matching literature, we define the probability of renters becoming home owners as *the outcome*; renters living in states that experienced bank deregulations (intra or inter) as *the treatment group*; and the other renters living in states that did not experience bank deregulations as *the comparison group*.

One advantage of matching estimation (compared to regression estimation) is that the key identifying assumption is weaker: the effect of covariates on the outcome need not be linear, as the matching method estimates the effect by matching households with the same covariates instead of a linear model for the effect of covariates. However, we should also note that matching is not a magic bullet to solve any unobservable variable bias. Similar to the regression, matching is based on the assumption that the source of selection bias is the set of observed covariates. That is, matching estimators would be biased if selection (into the treatment group) was based on unobservable variables.

Finding matches that are similar with respect to all relevant covariates, however, can be difficult if the number of covariates is large and the sample is relatively small. Nevertheless, Rosenbaum and Rubin (1983) prove that matching on *the propensity score*–which is the estimated probability of a renter becoming a home owner–suffices to adjust for the differences in the observed covariates. Matching on the propensity score is called propensity score matching, which is the technique we will use for the following estimation. The key estimator is called *the Average Treatment effect on the Treated (ATT)*, which has a similar interpretation to the marginal effects in the logit and the probit models: they measure the difference in the probability of becoming home owners between the renters living in states that experienced deregulation and the other renters living in the states that did not experience deregulation.

The matching process takes two steps. We first identify all renters in a given state. Then within that state, we match each renter in the treatment group with a renter in the comparison group. Renters are matched according to their propensity scores, which are estimated by a probit regression controlling for renters' demographic and socioeconomic status. We repeat these two steps for each state, and finally calculate the difference in the share of renters becoming home owners across the treatment group and the matched comparison group. The matching algorithm used in the second step is *the nearest neighbor matching*: for each renter in the treatment group, we find the "closest" renter in the comparison group, where the "closest" is defined by the distance between propensity scores.

The ATTs, and the corresponding standard errors, are reported in Column 4 of Table 8. Consistent with the regression estimations, the PSM results show that the inter-state deregulation has a larger impact than the intra-state deregulation on the probability of renters becoming home owners: the probability increases by 4.9 percentage points after the inter-state deregulation (compared to 5.7 percentage points in Column 3 of Table 3), and 2.3 percentage points after the intra-state deregulation (compared to 3.0 percentage points in Column 3 of Table 3). Both impacts are significant at the 1% level.

Identification of the PSM estimation relies on the hypothesis that the distributions of the propensity scores for the treatment group (i.e., renters in states experiencing the banking deregulations) and for the comparison group (i.e., renters in states not experiencing the banking deregulations) overlap with each other in a wide range. To test this hypothesis, we draw the distributions of the propensity scores for the treatment and the comparison groups in Figure 1 (for the intra-state deregulation) and Figure 2 (for the inter-state deregulation). A visual inspection of the two charts suggests that the hypothesis is satisfied, and therefore the PSM estimation is well identified.

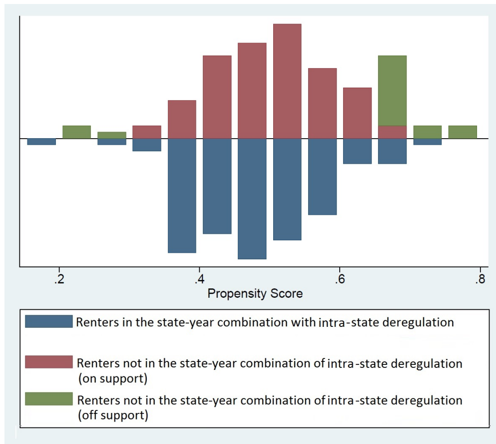

Figure 1: Propensity score distributions of treatment and comparison groups (Intra-state deregulation)

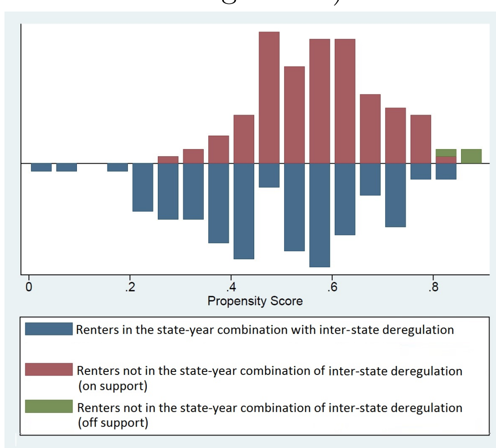

Figure 2: Propensity score distributions of treatment and comparison groups (Inter-state deregulation)

5 Possible Explanations

A number of theories can, in principle, produce the basic pattern of results that we observe in the data. In this subsection, we attempt to distinguish between these potential theories or explanations. There are at least two possible reasons why renters are more likely to become home owners after banking deregulations. The first is related to income; it could be that banking deregulations increase household income, especially for the low income households. With increased income, homes become more affordable for renters in the lower part of the income distribution, and therefore the transition rate increases. The second possible explanation is about the advances in credit risk pricing technology, especially the development of credit scoring technology. Bank deregulation increases competition among banks, and improves financial technology innovation. Technology innovation improves lenders' ability to more accurately price for credit risk and therefore offer credit to higher-risk individuals. In what follows, we examine these two explanations in more detail.

Strahan (2003) has provided strong evidence that banking deregulation has beneficial real effect on the economy, one component of which is household income. In addition, Beck, Levine and Levkov (2010) have also shown that bank deregulation boosts income for households with income below the median. If an increase in household income increases the probability of renters becoming home owners, bank deregulations may affect homeownership through its impact on household income. We have learned from Table 3 that income indeed has a positive impact on the transition rate from renters to owners. Therefore, to find evidence of the income channel, we are left to find out if banking deregulations have a positive impact on household income, especially for households in the lower part of the income distribution. To this end, we run a regression of the natural logarithm of the family income on the indicator variables of intra- and inter-banking deregulations and other observables, such as household demographic and socioeconomic status, and state and year fixed effects. The results are reported in Column 1 of Table 5. Consistent with previous literature, we find that the average household income increases by 23.0% after inter-state banking deregulation. Intra-state banking deregulation, however, has no significant impact on the average household income. Next, to find out if the impact of inter-state deregulation is larger for low income households, we run three quantile regressions for the 25th, 50th and 75th percentile of the income distribution, respectively. The results are reported in Columns 2 to 4 of Table 9. We omit the intra-state regulation in these quantile regressions. Indeed, the impact of inter-state banking deregulation on income is not uniform: the impact is largest on the 25th percentile of the income distribution (19.3% and significant at the 1% level), drops by two thirds on the 50th percentile of the income distribution (6.4% and insignificant at the 10% level), and is economically negligible and statistically insignificant on the 75th percentile of the income distribution. In sum, we find evidence that inter-state banking deregulation increases the likelihood of renters becoming owners by impacting renters' household income, especially for renters in the lower part of the income distribution.

Table 9: Impact of Bank Deregulations on Household Income

	(1)		(2)		(3)		(4)	
	OLS		Quantile regressions					
			25th percentile		50th percentile		75th percentile	
	Coef.	Sig. level	Coef.	Sig. level	Coef.	Sig. level	Coef.	Sig. level
Intra-state deregulation	0.025		N/A		N/A		N/A	
	(0.037)							
Inter-state deregulation	0.230	***	0.193	***	0.064		0.005	
	(0.010)		(0.064)		(0.049)		(0.029)	
Other controls:								
State & year fixed eff.	Yes		Yes		Yes		Yes	
Time-varying state var.	Yes		Yes		Yes		Yes	
Hhld characteristics	Yes		Yes		Yes		Yes	
Number of observations	9,330		9,330		9,330		9,330	

Note: All regressions are weighted using PSID core sample weights. All standard errors are clustered at the state level. All covariates are from the PSID except the time-vary state-level variables: median house price is from the Federal Housing Finance Agency, median household income from the Federal Reserve Bank of St. Louis, and unemployment rate from the Bureau of Labor Statistics. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Another potential reason why renters are more likely to become owners after banking deregulations is because banking deregulations intensify competition among banks, and improves financial technology innovation. Technology innovation improves lenders' ability to more accurately price for credit risk and therefore offer mortgage credits to higher-risk households. If this is the case, the impact of bank deregulation should be larger for higher-risk renters. To test for this hypothesis, we define higher-risk renters as those with debt-to-income ratios larger than 20 percent. The debt-to-income ratio does not include mortgages, as renters do not have mortgages. We then re-run our main regressions (i.e., the specification in Column 3 of Table 3) and control for the interactions of the indication variables of banking deregulations and the indication variable of high-risk renters. The results are reported in Table 10. Indeed, both intra- and inter-state deregulations have larger impacts on higher-risk renters: The impact of intra-state deregulation on the likelihood or renters becoming homeowners is 2.6 percentage points and insignificant for lower-risk renters, but doubles to 5.4 percentage points for higher-risk renters. Similarly, the impact of inter-state deregulation is 5.3 percentage points for lower-risk renters, but more than doubled for higher-risk renters to 11.1 percentage points. These results provide strong evidence that the impact of bank deregulations (both intra- and inter-state) is in part through its impact on technology, so that higher-risk renters benefit more from bank competition after the deregulations.

6 Concluding Remarks

During 1970s-1990s, most states in the U.S. removed restrictions on intra-state branching and inter-state banking, which intensified bank competition and increased credit supply. In this paper, we study the real effect of banking deregulations on home ownership at the household level. By following a sample of renters in the Panel Study of Income Dynamics (PSID), we find strong evidence of a positive impact of banking deregulations on the likelihood of households becoming home owners: all else being equal, renters in states that experience

Table 10: Impact of Bank Deregulations on the Probability of Renters Becoming Home Owners (Low-risk vs high-risk renters)

	Marginal effect	Coef.	Sig. level
For low-risk renters (with debt-to-income ratios $\leq$ 20%)			
Intra-state deregulation	0.026	0.165	
		(0.116)	
Inter-state deregulation	0.053	0.333	***
		(0.074)	
For high-risk renters (with debt-to-income ratios > 20%)			
Intra-state deregulation	0.054	0.337	***
		(0.069)	
Inter-state deregulation	0.111	0.696	***
		(0.066)	
Other controls:			
State and year fixed effects		Yes	
Time-varying state variables		Yes	
Household characteristics		Yes	
Log likelihood		-29,580	
Number of observations		4,060	

Note: All regressions are weighted using PSID core sample weights. All standard errors are clustered at the state level. All covariates are from the PSID except the time-vary state-level variables: median house price is from the Federal Housing Finance Agency, median household income from the Federal Reserve Bank of St. Louis, and unemployment rate from the Bureau of Labor Statistics. * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

banking regulations are 8.7 percentage points more likely to become home owners. Given that the unconditional transition rate from renters to home owners is 26.3 percentage points, the 8.7 percentage-point increase indicates that banking deregulations, by removing the barriers to branching within state and to out-of-state bank entry, can explain as high as a 33% increase in the likelihood of households becoming home owners. In addition, the impact is larger on households with low income and high debt-to-income ratios. Our estimated impacts are larger than those estimated from state-level data, suggesting that the heterogeneous effects among households are important towards home ownership. The results are robust to sample-selection bias and functional misspecifications.

We explore two potential channels underlying these findings. Consistent with the prior literature, first, we find that the banking deregulations have boosted incomes in the lower part of the income distribution, which increases the capacity for low-income households to qualify for mortgage loans. Second, banking deregulations allow mortgage credits to be extended to more households, most importantly to higher-risk households. This is consistent with the view that banking deregulations increase credit supply through the use of new screening technology to more risky households.

The identification of the two channels has important policy implications, especially given a large drop in homeownership rate since the recent financial crisis. Our findings suggest that government policy aiming to increase credit supply will have a significant effect on improving the homeownership rate.

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