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Time Preferences, Mortgage Choice and Mortgage Default

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The global economy is in the midst of a recession triggered by the ongoing pandemic of a novel coronavirus disease (COVID-19). The shutdown of the economy and a surge in the unemployment rate also cause stress to the US housing and mortgage system and create significant impacts on the default behaviour of mortgage borrowers. The potential rise in mortgage defaults may renew the long-standing debate over the empirical observation of why some mortgage borrowers do not default as “ruthlessly” as the finance theory predicts. In this paper, we propose an alternative theory to explain for the different default behaviours among mortgage borrowers. We hypothesize that the difference among time preferences across mortgage choices is one of the underlying factors that causes the heterogeneity in default patterns. Borrowers can either have a present-biased preference (overvaluing immediate outcomes), or a time-consistent preference (with standard exponential discounting). Borrowers with a present-biased preference are more likely to accept back-loaded mortgages that minimize up-front costs, even though this increases their risk of going “underwater” and entering default when an adverse shock, such as the one from the ongoing pandemic, occurs.

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Keywords

Mortgage Default, Mortgage Choice, Heterogeneity, Present-Biased Preference, Dynamic Inconsistency, Covid-19, Pandemic

1. Introduction

The global economy is in the midst of a recession triggered by the ongoing pandemic of a novel coronavirus disease called COVID-19. According to the United States (US) Bureau of Labor Statistics, the nationwide unemployment rate in the US jumped to 14.7 percent in April 2020 (versus an all-time low of 3.7 percent in 2019). The highest unemployment rate recorded was 28.2 percent in the state of Nevada. The surge in the unemployment rate has also created significant stress on the US housing and mortgage system and resulted in the default tendency of mortgage borrowers. The increasing cases of mortgage defaults may revitalize the long-standing debate in the literature on mortgage default over the empirical observation on why some mortgage borrowers do not default as "ruthlessly" as the finance theory predicts.

The global financial crisis of 2008 triggered by the stunning rise of subprime mortgage delinquencies led to the re-evaluation of mortgage defaults and foreclosures. During the crisis, millions of homeowners in the US "walked away" and allowed the foreclosure of their home. Moreover, according to the negative equity report compiled by CoreLogic, owners of 11.1 million residential properties were in negative equity (i.e., they were "underwater") and at the risk of foreclosure by the end of 2011.[1] Table 1 lists the ten states with the highest levels of negative equity and near negative equity in the US.[2] Compared to borrowers who simply "walked away" and those in default, most underwater homeowners continued to make their mortgage payments. However, it is difficult to know beforehand which borrowers will be in default because there is significant heterogeneity among them. This leads to the long-standing puzzle in the mortgage default literature – why some homeowners choose to default on their mortgages, while others do not.

This paper provides an alternative theory to explain for the different default behaviour of mortgage borrowers. The study examines whether heterogeneity in the time preferences of borrowers correlates with their decision to default on their mortgage payments. The time preferences of borrowers are measured by

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[1] http://www.corelogic.com/about-us/news/corelogic-reports-negative-equity-increase-in-q4-2011.aspx Accessed March 15, 2012.

[2] Properties that are in negative equity, where the borrower owes more on their mortgage than the current market value of the property, are often termed as being "underwater" or "upside down". Mortgages that are within five percent of being in a negative equity position are defined by CoreLogic as being "near negative equity".

using their choice of mortgage type. In particular, the study investigates borrowers who demonstrate present-biased preference. Specifically, we examine borrowers who are more likely to accept back-loaded mortgages that minimize up-front costs and place them at a higher risk of becoming an underwater homeowner. Such borrowers may default following adverse shocks in home prices and mortgage systems triggered by the ongoing global pandemic.

Table 1 Negative Equity in Selected US States.

State	Negative Equity Share	Near Negative Equity Share
Nevada	56.90%	5.30%
Florida	42.10%	4.10%
Arizona	38.60%	5.10%
Georgia	35.60%	6.30%
Michigan	32.00%	4.80%
California	28.30%	4.50%
Illinois	25.40%	4.60%
Ohio	23.80%	5.70%
Maryland	22.90%	4.80%
Idaho	22.30%	5.30%

Notes: This table presents the ten states with the highest levels of negative equity and near negative equity in the United States. Negative equity is often used with reference to "underwater" or "upside down" homeowners, which means that borrowers owe more on their mortgage than the home is worth. In other words, the mortgage value exceeds the property value. Negative equity can occur because of a decline in property value, an increase in mortgage debt, or a combination of both. Near negative equity is when mortgages are within five percent of being in a negative equity position, which is defined by CoreLogic. Source: Negative Equity Summary Report of CoreLogic, Jan-2013.

The contingent claims models, which are developed by Black and Scholes (1973), Merton (1973), Cox, Ingersoll and Ross (1985), provide a useful framework for analyzing the behaviour of borrowers, in which prepayment is treated as an American call option and default as a compound put option. The "pure" option-theoretic mortgage pricing models assume that a well-informed borrower will default immediately when the mortgage value exceeds the value of his/her property at any time during the loan term (Titman and Torous 1989; Kau, Keenan and Kim 1994). These models assume a perfectly competitive market without any transaction or reputation costs and no exogenous reasons for residential mobility. Although a frictionless market is an ideal case, negative equity may be a necessary but not sufficient condition to trigger default (Vandell 1995; Deng, Quigley and Van Order 2000; Bajari, Chu and Park 2008). Evidence shows that a substantial number of borrowers are unlikely to default as "ruthlessly" as the option theory predicts. White (2010) argues that not all homeowners who were underwater on their mortgage walked away from their home immediately during the recent financial crisis, including those who lived in non-recourse states, such as California and Arizona. [3] Although such behaviour may appear irrational at face value, the homeowners who stayed and those who walked away all struggled with the same decision: whether they would continue to pay their mortgage.

Many empirical studies have tried to explain this “irrational” phenomenon by using an option-based framework. The anecdotes that underlie these studies emphasize that the transaction costs that result from default are pervasive and significant (Stanton 1995; Archer, Ling and McGill 1996; Deng, Quigley and Van Order 1996; Harding 1997).[4] These studies assume that transaction costs, which include moving costs, reputational issues, and default penalties, are high enough to deter homeowners from leaving their home. In addition to the economic considerations of transaction costs, recent attention has been given to the emotional constraints of strategic default. Guiso, Sapienza, and Zingales (2013) use survey data to document that social and moral considerations may play a partial role in explaining the willingness of homeowners to continue to pay their underwater mortgage. White (2010) also argues that the shame or guilt associated with foreclosure and fear over the perceived consequences of foreclosure discourage underwater homeowners from defaulting.

The role of transaction costs is important for determining the exercise of both default and prepayment options. What causes default borrowers to accept the economic and emotional transaction costs that accompany their decision to default? The empirically unobserved heterogeneity of mortgage borrowers has been extensively discussed in the literature, but only as an unproven assumption. For example, Deng, Quigley and Van Order (2000) assume that borrowers are heterogeneous agents who form discrete groups, and Hall (2000) assumes that these agents have different distributions of underlying hazards. Stanton (1995) and others have also argued that heterogeneity exists within mortgage pools. Deng and Quigley (2002) present a model of borrower behaviour in the mortgage market in which some correlates of the unobserved heterogeneity of individual borrowers are observed, without being limited by specifying a restrictive functional form or an arbitrary constellation of mass-points of population heterogeneity. However, researchers have been unable to provide a theoretical framework for this unobserved heterogeneity or explain its origins.

Our study builds on the well-developed economic literature on time preferences to explain for the unobserved heterogeneity in mortgage default decisions. Two types of time preferences are found for borrowers, with corresponding discounting factors: present-biased preference (overvaluing immediate

[3] In non-recourse states, lenders cannot pursue defaulting homeowners for a deficiency judgment. While lenders can recover some of their losses by foreclosing on the property, they cannot sue borrowers for additional funds. If the foreclosure sale does not generate enough funds to pay the loan, the lenders must accept the losses.

[4] For an explicit discussion about these transaction costs, see Kau, Keenan and Kim (1993).

outcomes), and time-consistent preference (standard exponential discounting). The key distinction between these two is the presence and absence of a “present bias”. Individuals with present-biased preference prefer immediate gratification, and, as a result, are more likely to minimize their up-front costs and postpone their mortgage payment. They are thus more likely to select back-loaded mortgages, such as interest-only loans. This selection is more likely to place them at a higher risk of going underwater and defaulting following negative home price shocks.

We hypothesize that naïve borrowers with present-biased preference are more likely to select interest-only loans, which allow them to enjoy the immediate benefits of homeownership and postpone their mortgage payment costs. Sophisticated borrowers with present-biased preference, on the other hand, are fully aware of their future self-control problems, and know their future preferences exactly, even though these may differ from their current preferences. Therefore, they are smart and more likely to choose 30-year adjustable-rate loans. In contrast, borrowers with time-consistent preference tend to choose 30-year fixed-rate loans, which are fully amortizing mortgage loans where the interest rate on the note remains the same through the term of the loan.

We examine the correlation between the time preferences of borrowers and their mortgage choice and default decisions. The study uses individual loan-level mortgage data principally collected by Moody’s-BlackBox Logic (BBx), and a home loan application and origination data managed by the Home Mortgage Disclosure Act (HMDA) in the US. The logistic regression model includes fixed effects of year of origination, year of termination, and the state in which the property is located. First, we compare the default behaviour of naïve borrowers who select an interest-only loan, against those who choose a 30-year fixed-rate loan. The results indicate that borrowers with a 5-year interest-only loan are 36.8% more likely to default than those with a 30-year fixed-rate mortgage. In addition, borrowers with a 10-year interest-only loan are 38.1% more likely to default than dynamically-consistent borrowers who choose a 30-year fixed-rate loan.

We further study the default behaviour of borrowers who choose a 30-year adjustable-rate loan relative to those who select a 30-year fixed-rate loan. We find that sophisticated borrowers who choose a 30-year adjustable-rate loan are 34.7% more likely to default than borrowers who select a 30-year fixed-rate loan. In other words, the default rate of sophisticated borrowers with present-biased preference is higher than borrowers with time-consistence preference.

Finally, we examine the default behaviour of both interest-only and 30-year adjustable-rate loans relative to those who select a 30-year fixed-rate loan. The results indicate that present bias is highly correlated with mortgage default, and borrowers who show present-biased preference in their choice of mortgage have a substantially higher probability of default. Borrowers with a 5-year interest-only loan are 32.3% more likely to default than those who select a 30-

year fixed-rate loan. At the same time, borrowers with a 10-year interest-only loan are 32.3% more likely to default than dynamically-consistent borrowers who choose a 30-year fixed-rate loan. Besides, the default probability of borrowers with a 30-year adjustable-rate loan is 31.8% higher than that of borrowers who choose a 30-year fixed-rate loan. The association between present bias and mortgage default holds when controlling for other loan characteristics and housing prices. Moreover, all of the results hold after using propensity score matching (PSM), based on borrower characteristics (including income, race, and sex) and loan characteristics (e.g., original loan balance, location of the property, origination year, etc.) for different types of loan. These results are, therefore, the first direct support for the claim that the mortgage default decisions of borrowers are related to their different time preferences.

This paper contributes to several strands of the existing literature. First, the work complements the broader literature on mortgage default. The study presents an alternative theory to explain the origins of the unobserved heterogeneity in the default decisions of mortgage borrowers. Under the conventional assumption of a "frictionless" mortgage market, Foster and Van Order (1984) find that borrowers do not default "ruthlessly". They exercise the put option of default if the value of their house fell below the mortgage value by an amount equal to the net transaction cost. However, a number of empirical studies have documented that a pure option-based theory cannot fully explain for mortgage default behaviour. They find that the impact of transaction costs on the decision to default on a mortgage is important (see, for example, Cunningham and Hendershott 1984; Foster and Van Order 1984; Vandell and Thibodeau 1985; Quigley and Van Order 1991; Lekkas, Quigley and Van Order 1993). In addition to the above studies that conjecture the presence of transaction costs, some other studies try to test the importance of transaction costs and incorporate them into default risk modeling. For example, Lekkas et al. (1993) and Quigley and Van Order (1995) explicitly test "frictionless" models and validate the importance of transaction costs aside from equity position.[5] Deng, Quigley and Van Order (2000), Deng, Pavlov and Yang (2005), and Clapp, Deng and An (2006) stress the importance of borrower and spatial heterogeneity associated with transaction costs.[6] Kau, Keenan and Kim (1993) and Kau and Slawson (2002) include both transaction costs and suboptimal termination into mortgage pricing models.

At the same time, transaction costs are complicated and differ across mortgage holders, thus creating significant unobserved heterogeneity among borrowers. The role of unobserved heterogeneity in explaining mortgage termination has also attracted much attention. Richard and Roll (1989), Schwartz and Torous

[5]Clauretie (1987) explicitly includes non-equity variables, like costs of foreclosure and unemployment rate, and show their significance for rates of foreclosure.
[6]Other examples that incorporate market imperfections to "frictionless" models include Vandell (1993), Van Order and Zorn (2000), Pavlov (2001), Calhoun and Deng (2002), and Goldberg and Harding (2003).

(1989), and Archer, Ling and McGill (1996) all suggest the use of ad hoc variables to analyse mortgage pools and address heterogeneity within the mortgage pools. Stanton (1995, 1996) extended previous research to manage the heterogeneity between mortgage pools. Deng, Quigley and Van Order (2000), and Clapp, Deng and An (2006) consider the issue of unobserved heterogeneity in the context of hazard modeling. They explicitly account for the unobserved heterogeneity among borrowers by adding mixed hazard rate to a discretely distributed mass point. Although empirical studies have used transaction costs to explain the differences in default behaviour, there is no unifying theory that explains for the underlying unobserved heterogeneity of borrowers.

This paper also adds to the literature on individual different time preferences, which has been addressed in both psychology and behavioural economics. Past research has documented that individual differences in time preference are an important predictor for many life choices. For example, there are studies on gym contracts (DellaVigna and Malmendier 2006), smoking (Gul and Pesendorfer 2007), body-mass index (Smith, Bogin and Bishai 2005, Courtemanche and Carden 2011), savings for retirement (Carroll et al. 2009), and credit card debt (Laibson, Repetto and Tobacman 2007; Meier and Sprenger 2010; Kuchler 2013). Besides, Krusell, Kuruscu, and Smith (2010) analyze the effects of present bias on optimal taxation. DellaVigna and Paserman (2005) use the present bias preference to explain for individual job search behaviours. However, researchers have not studied the effects of present bias on mortgage choice and default, and relatively few papers on mortgage choice and default have differentiated between naïve and sophisticated individuals. In this paper, heterogeneous time preferences among borrowers, as indicated by their mortgage choice, are used to explain the default behaviour of present-biased borrowers. Different mortgage types are also used to differentiate between naïve and sophisticated borrowers.

The rest of this paper is organized as follows: Section 2 presents a typical form of present-biased preference (i.e., quasi-hyperbolic), following the original work of Phelps and Pollak (1968) (later applied by Laibson (1994, 1997, 1998) and other papers); Section 3 elaborates on time preferences and mortgage choices; Section 4 describes the data used in this paper; Section 5 discusses the default behaviour for different types of mortgages by using a logistic model, and Section 6 concludes the paper.

2. Present-Biased Preference

Traditional intertemporal preference models in economics have captured the impatience of agents by using exponential discounting. This approach explicitly assumes that preferences are intertemporally consistent. However, this standard economic assumption may not be applicable in all instances when we are considering trade-offs between two future moments. Specifically, individuals with present-biased preference tend to give relatively more weight to nearer moments in the future as they get closer, and their intertemporal preferences are time-inconsistent (O'Donoghue and Rabin, 1999a).

One way of modeling present-biased preference is to use "quasi-hyperbolic discounting" or "(β, δ)-preference", which was developed initially by Phelps and Pollak (1968), and was later applied by Laibson (1994, 1997, 1998) to capture self-control problems within an individual. This method is widely used in the literature (e.g., O'Donoghue and Rabin, 1999a, 1999b, 1999c, 2001; Fischer, 2001) and will be used in this paper.

Let u_t be the instantaneous utility that the borrower obtains in period t, and $U(u_t, u_{t+1}, u_{t+2}, \ldots, u_T)$ be the intertemporal preference function of the borrower from the perspective of period t. Borrowers are assumed to have a quasi-hyperbolic preference. Time is divided into two periods: the present period (t) and all future periods (beginning from t+1 to T). The intertemporal preference function for borrowers with present-biased preference is expressed as:

$$U(u_t, u_{t+1}, u_{t+2}, \ldots, u_T) = \delta^t u_t + \beta \sum_{\tau=t+1}^{T} \delta^\tau u_\tau \qquad (1)$$
$$\text{for } t \in [1, T];\ 0 < \delta \leq 1;\ 0 < \beta \leq 1$$

As in the standard exponential discounting model, the parameter δ represents the "time-consistent" long-run discounting factor. In this intertemporal preference model, an additional parameter β is added to the standard time-consistent model for the future period to capture the "bias for the present" of an individual; i.e., the preference of the agent for the current and overall future periods. There are two types of β: $\beta = 1$ and $0 < \beta < 1$.

For $\beta = 1$,

$$U(u_t, u_{t+1}, u_{t+2}, \ldots, u_T) = \sum_{\tau=t}^{T} \delta^\tau u_\tau \qquad (2)$$

The intertemporal preference function is reduced to a standard exponential discounting utility function with time-consistent intertemporal preference (the discrete version). Under this time preference, borrowers treat the present period, and all future periods the same.

For $0 < \beta < 1$,

$$U(u_t, u_{t+1}, u_{t+2}, \ldots, u_T) = \delta^t u_t + \beta \sum_{\tau=t+1}^{T} \delta^\tau u_\tau \qquad (3)$$

This function parsimoniously captures present-biased preference, and greater weight is assigned to the present relative to the future. The β-parameter in this model thus fully captures the dynamic-inconsistency suggested by present-biased preference (O'Dognohue and Rabin, 1999a, 1999b 1999c).

If a time-inconsistent preference is assumed, the individual at each time period is modeled as a separate agent who maximizes utility in accordance with her current preference. At the same time, his/her "future selves" will control his/her future behaviour based on the prevailing preferences in the future (O'Donoghue and Rabin, 1999a). An important question that follows this assumption is: what does an individual believe about the preferences of his/her future self? A crucial insight from the present-biased preference perspective is the distinction between naïve and sophisticated individuals. A sophisticated individual is fully aware of his/her future self-control problems, and exactly knows the preferences of his/her future self , even though they may differ from those of the current self. In contrast, a naïve individual does not anticipate his/her future procrastination and is thus entirely unaware of his/her future self-control problems. This contributes to his/her belief that his/her future preferences will be identical to the current ones. Under such a distinction, the choices of naïve and sophisticated individuals are different.

3. Time Preferences and Mortgage Choice

Selecting a mortgage is a consequential consumer choice that highlights the role of time preferences in determining outcomes.[7] While a mortgage is often complex and differs along many dimensions, they can be broadly classified into two main categories based on their repayment structure: back-loaded and front-loaded mortgages. The second dimension of interest is the length of repayments. Mortgage contracts typically involve repayment periods of 30 years, but can also be structured for shorter periods, such as 10 years. The selection of a particular payment structure is an indication of the intertemporal preferences of the borrower.[8]

A fixed-rate mortgage (FRM) is a fully amortizing mortgage loan where the interest rate on the note remains the same throughout the term of the loan, as opposed to "floating" loans in which the interest rate may vary. As a result, the payment amount and loan duration of an FRM are fixed, and the person who is responsible for paying back the loan benefits from a consistent, single payment and the ability to plan a budget based on this fixed cost. The constant discounting for FRMs implies that intertemporal preferences are time-

[7] Carroll et al. (2009) model the optimal policies of 401(k) savings for present biased consumers. DellaVigna and Malmendier (2006) study the contract choice of present biased consumers among health clubs, and conclude that the preferences of consumers among contracts are important. Prelec and Loewenstein (1998) illustrate how payment and consumption events can be optimally timed and linked.

[8] The mortgage choice of borrowers can be influenced by multiple players in the mortgage markets. The hypotheses raised in the paper capture parts of the whole system. The implications might change if the broader general equilibrium is fully considered.

consistent, which means that any decision that the individual makes for him/herself in advance will remain valid as time passes. Later preferences "confirm" earlier preferences. Therefore, borrowers with a time-consistent preference (standard exponential discounting) will choose FRMs.

An interest-only loan is a loan in which, for a set term, the borrower pays only the interest on the principal balance, with the principal balance unchanged. At the end of the interest-only term, the borrower may enter an interest-only mortgage, pay the principal, or (with some lenders) convert the loan to a principal and interest payment (or amortized) loan at his/her own will. Mortgages with interest-only loans are particularly appealing to present-biased individuals because they have lower upfront costs in return for greater later costs. In addition, with the absence of self-control, interest-only loans are more likely to be selected by naïve borrowers who are entirely unaware of their future self-control problems to minimize their up-front costs and postpone payment of their mortgage.

In contrast, "sophisticated" borrowers who have a present-biased preference, or suffer from short-term temptations and are aware of the consequences, are likely to avert temptation and behave more rationally. When selecting a mortgage, sophisticated borrowers might be concerned about the minimum upfront cost and the corresponding future over-payments. They may refrain from interest-only loans so that they are able to resist temptation in the future. This means that, unlike naïve borrowers, sophisticated borrowers will not choose interest-only loans. However, they will also not choose fixed-rate loans, which are preferred by time-consistent borrowers. An adjustable-rate mortgage (ARM) is a mortgage loan in which the interest rate on the note is periodically adjusted based on an index that reflects the cost to the lender of borrowing on the credit markets. ARM loans are similar to interest-only loans, in that they allow borrowers to enjoy minimal up-front costs, and differ from FRM loans, in that loan repayments are not a consistent amount. Therefore, sophisticated borrowers with self-control will be more likely to choose an ARM.

4. Data

Two main sources of data are used in this paper: individual loan-level mortgage data, from the BBx, and a database of home loan applications and originations collected by the HMDA.

Moody's BBx is a private company that provides a comprehensive, dynamic dataset with information about twenty-one million privately securitized subprime, Alt-A, and prime loans in the US. These loans account for about ninety percent of all privately securitized mortgages. The BBx data, obtained from mortgage services and securitization trustees, provide static information taken at the time when the mortgages originated. For example, the mortgage contract date, original loan amount, initial loan-to-value (LTV) ratio, FICO credit scores of borrowers, mortgage service name, mortgage contract interest rate, mortgage term, type of interest rate, state, region, and major metropolitan area in which the property is located. Besides, the BBx data also include time-varying data on monthly payments, mortgage balances, current LTV ratio, and delinquency status.

The HMDA database is available at the loan application level, which is reported annually.[9] The data serve as a record of the purpose of borrowing (home purchase, refinancing, or home improvement), loan amount, final status of each application (denied, approved, or originated), and, in the case of originated loans, whether the loan was sold to the secondary market within the year. The database also includes the attributes of the borrowers (race, gender, income, and homeownership status), and the location of the property.

The analysis in this paper is confined to first-lien mortgage loans issued between 1995 and 2011 and includes loans that were either closed or still active in the third quarter of 2012. The analysis is confined to 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. After removing mortgages with incomplete information in terms of the LTV ratio, original loan balance, FICO score, and other key information, the final sample includes 3,058,413 individual mortgages.

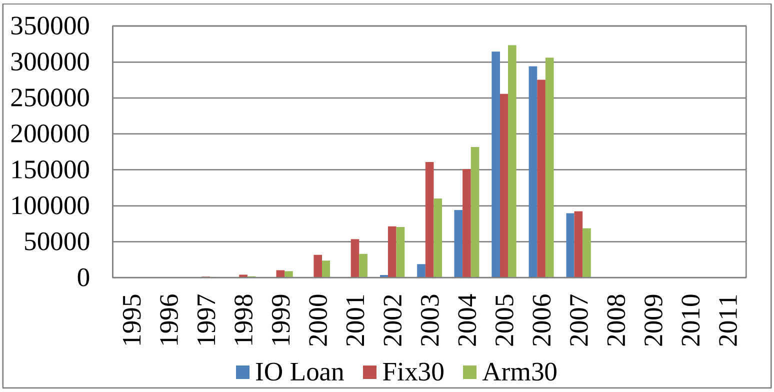
Figure 1 shows the distribution of loan originations over the years. Generally, the volume of all loans increased tremendously between 2001 and 2006. In 2005, the number of originations of interest-only loans and adjustable-rate loans peaked. The number of fixed-rate loan originations peaked in 2006. Before 2003, the origination of fixed-rate loans dominated the loan market, which changed after 2004. The origination of interest-only and 30-year adjustable-rate loans progressed very quickly after 2004. Moreover, the number of interest-only loans grew at a faster rate than that of both fixed-rate and adjustable-rate loans. After the financial crisis, the origination of all kinds of loans decreased substantially.

Figure 2 focuses on loan origination growth in four states (i.e., California, Florida, Arizona, and Nevada). Consistent with the dramatic growth, as shown in Figure 2-1, the origination of all kinds of loans grew substantially between 2001 and 2006 in these four states. In addition, the origination of interest-only loans increased particularly fast in California (CA), Arizona (AZ), and Nevada (NV). In these three states, the origination of interest-only loans in 2005 and 2006 was more than twice the number of 30-year fixed-rate loans. Consistent

[9] The HMDA, enacted by Congress in 1975 and implemented by the Federal Reserve Board, requires lending institutions to report public loan data. The lending institutions mainly include banks, savings associations, credit unions, and other mortgage lending institutions.

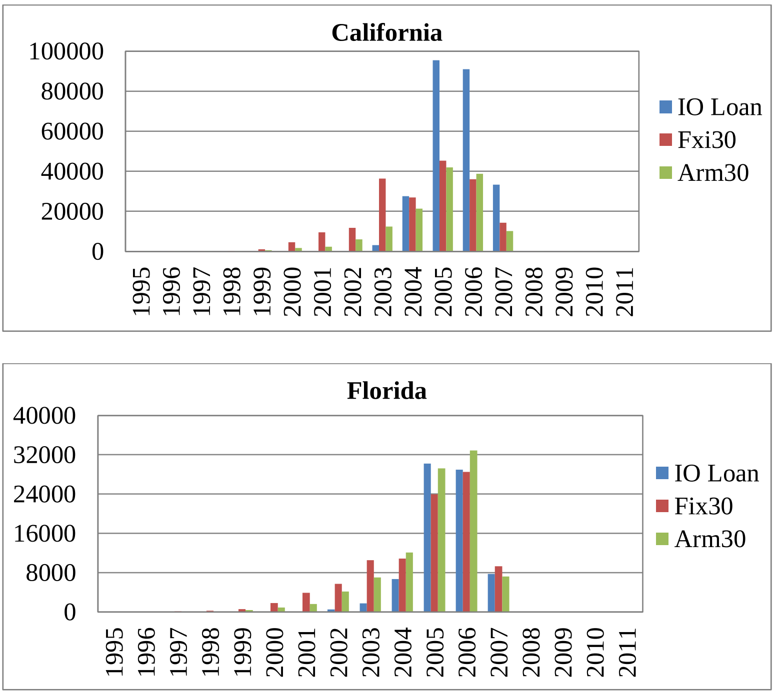
with Figure 1, the number of originations for all kinds of loans dropped sharply since the financial crisis began.

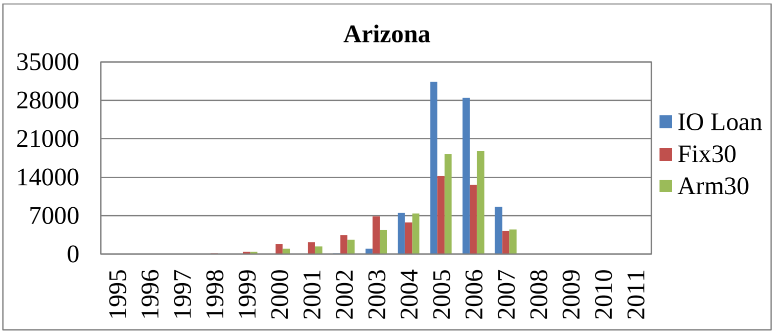
Figure 1 Frequency Distribution by Origination Year

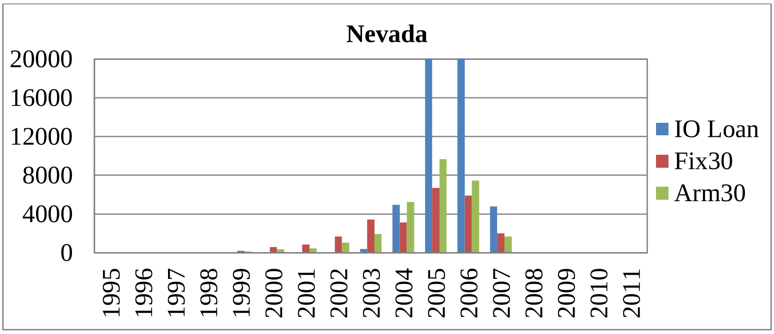


Note: This figure shows the frequency distribution of all kinds of loan originations for the full sample. Y-axis denotes the frequency of origination, while X-axis denotes the year. Three loan types are included in this sample: interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans.

Figure 2 Frequency Distribution by Origination Year: Four States







Note: This figure shows the frequency distribution of all kinds of loan originations for four states: California (CA), Florida (FL), Arizona (AZ), and Nevada (NV). Three loan types are included in this sample: interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. Y-axis denotes the frequency of origination, while X-axis denotes the year.

Table 2 shows the summary statistics of the BBx dataset. Information on three types of first-lien mortgage loan originations between 1995 and 2011 is shown: interest-only loans (5-year and 10-year loans), 30-year fixed-rate loans, and 30-year adjustable-rate loans. Of these, 26.7% of the loans are interest-only loans, with 10.62% being 5-year interest-only loans and 16.08% 10-year interest-only loans. About one third or 36.31% of the loans are 30-year fixed-rate loans, and 36.99% are 30-year adjustable-rate loans. Borrowers have an average FICO score of 663.52, and borrowed up to 79.15% of the property value (LTV) in the sample.

Columns (2) to (4) show the summary statistics for each type of loan separately. Nearly 40% of interest-only loans are 5-year interest-only loans. Loans and borrowers have distinct characteristics for each type of loan. The average amount borrowed is the highest among interest-only loans, nearly two times the amount borrowed for 30-year adjustable-rate loans. The FICO scores for interest-only loans are the highest, with an average of 699.496. Borrowers who opted for 30-year adjustable-rate loans have the lowest FICO score of 617.575. The average amount borrowed for interest-only loans and 30-year fixed-rate loans is similar, and is up to 77% of the value of the property. However, the average amount borrowed for 30-year adjustable-rate loans is much higher than other types of loans, which is up to 82.5% of the value of the property.

Table 2 Summary Statistics of Variables

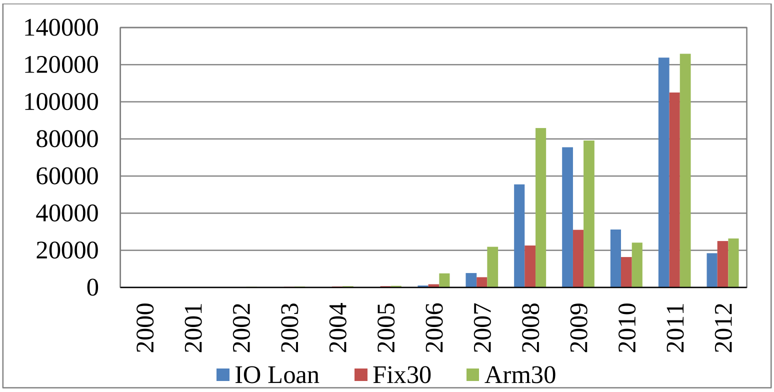
	Original Total	IO. Loans	FIX30	ARM30
IO5	10.62%	39.77%		
IO10	16.08%	60.23%		
FIX30	36.31%			
ARM30	36.99%			
Current Interest Rate	7.001	5.969	6.984	7.790
Original Loan Balance	225143.32	312080.52	216238.08	171130.41
FICO Score	663.52	699.496	683.866	617.575
OrigLTVRatioCalc	79.150	77.176	77.187	82.502
ownerocc	84.44%	81.68%	81.36%	89.45%
low_no_doc	45.22%	60.37%	45.88%	33.62%
subprime	29.34%	8.85%	18.89%	54.38%
Duration	56.606	54.444	62.426	52.452
Log_MHPI	5.168	5.203	5.150	5.161
Sample size	3,058,413	816,569	1,110,638	1,131,206

Notes: This table presents the summary statistics of the BlackBox dataset. The sample includes 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. The values reported in the table are the average values of the variables by full sample, interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. "*IO5*" is the 5-year interest-only loans, that takes the value of one for 5-year interest-only loans, and zero otherwise. "*IO10*" is the 10-year interest-only loans, that takes the value of one for 10-year interest-only loans, and zero otherwise. "*FIX30*" is the 30-year fixed-rate loans, that takes the value of one for 30-year fixed-rate loans, and zero otherwise. "*ARM30*" is the 30-year adjustable-rate loans, that takes the value of one for 30-year adjustable-rate loans, and zero otherwise. "*Original Loan Balance*" is the amount of principal on the closing date of the mortgage. "*FICO Score*" refers to the Fair Issac's score of borrower at the time of loan origination. "*OrigLTVRatioCalc*" refers to the ratio of the original loan amount to the property value at loan origination. "*Ownerocc*" takes the value of one, if the property type is owner-occupied, and zero otherwise. "*low_no_doc*" takes the value of one, if the document type of the loan is low- or no-documentation, and zero otherwise. "*Subprime*" equals to one, if the loan is subprime, and zero otherwise. "*Duration*" is the duration of the loans measured by months, which is defined as the elapsed time from origination to the end of the sample period, or the first classification as being prepaid or delinquent at least 60 days. "*Log_MHPI*" is the logarithm for the quarterly FHFA house price index.

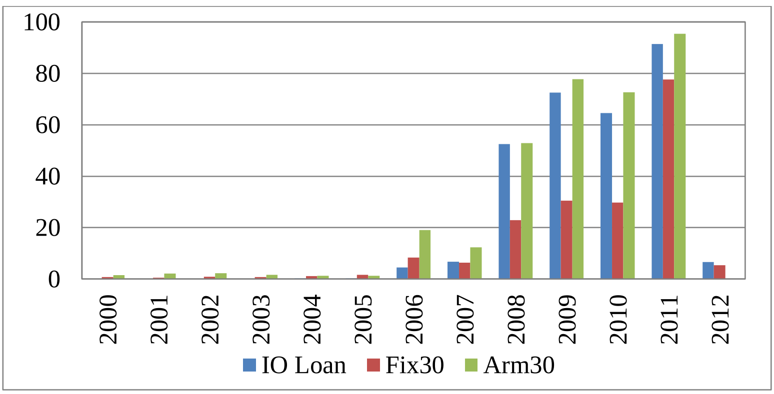
Figure 3 suggests the default pattern for each type of loan over the period being studied. The default rate for each type of loan increased dramatically after the recent financial crisis, especially for interest-only and 30-year adjustable-rate loans. Both the default frequency and default percentage peaked in 2011 for all kinds of loans. In addition, it can be seen from both the frequency and percentage of default distributions, that the default rate for interest-only and 30-year adjustable-rate loans is much higher than that for 30-year fixed-rate loans from 2008 to 2011. Figure 4 suggests that the default patterns in the four states are consistent with the full sample. Particularly, the default frequency for interest-only loans after the recent financial crisis is much higher than the default frequency for other types of loans in California, Arizona and Nevada.

Figure 3 Default Distribution over Years

A: Frequency Distribution of Default by Year



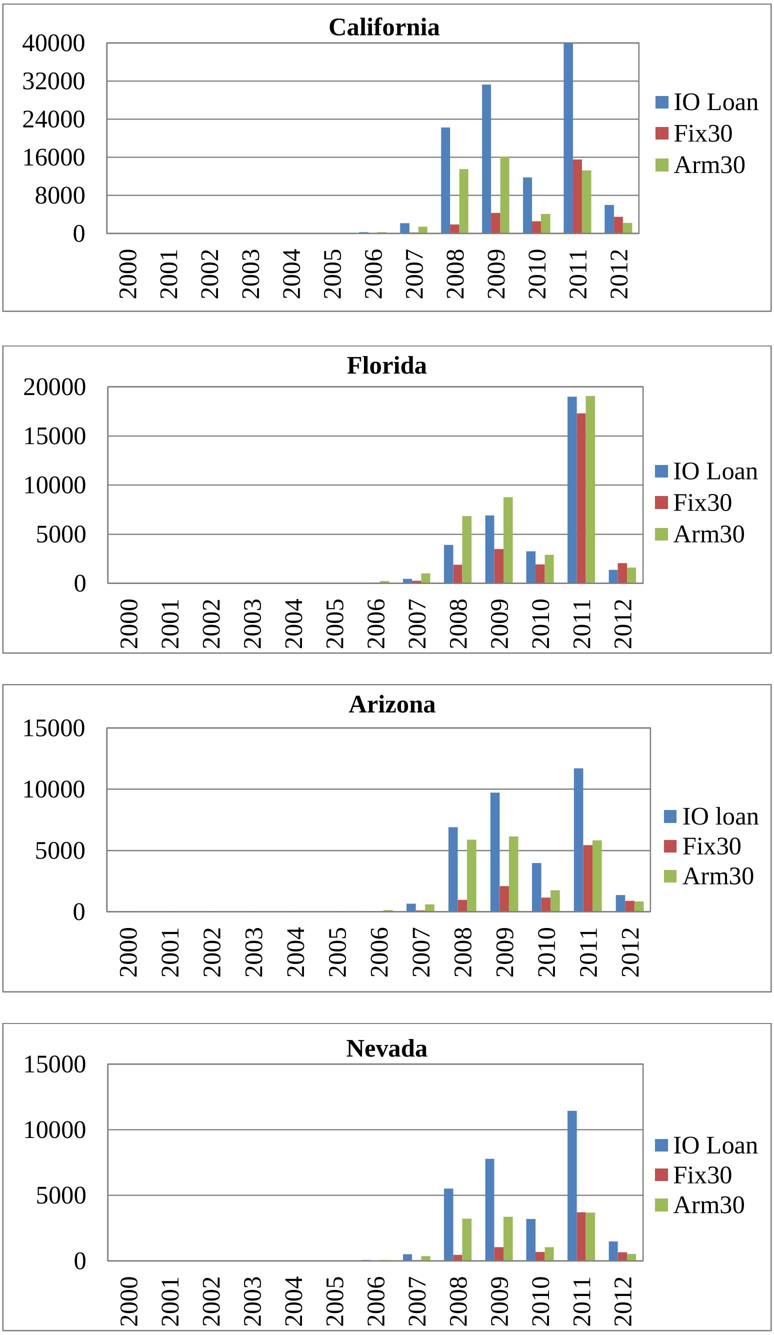
B: Percentage of Default by Year



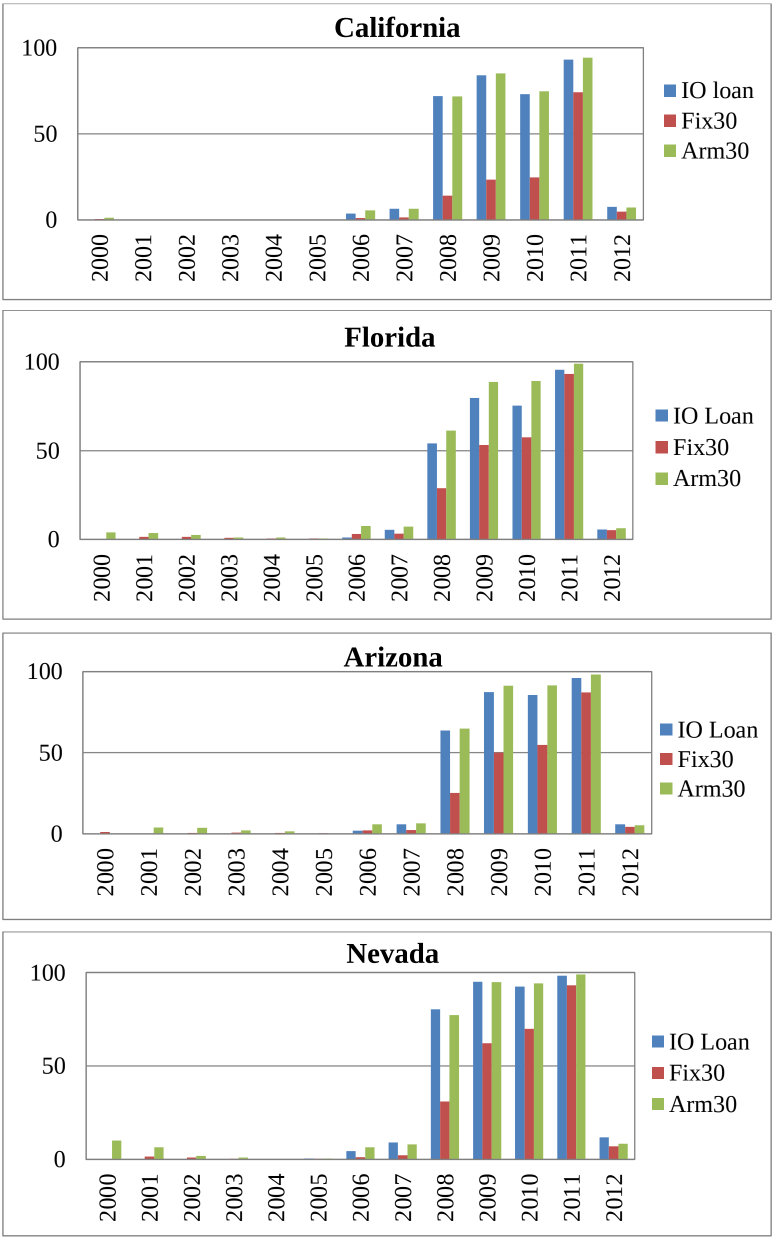
Note: This figure shows the frequency and percentage of default distribution for all kinds of loans over the years. In Panel A, the y-axis denotes the frequency of default loans, while x-axis denotes the year. In Panel B, the y-axis denotes the default rate, while X-axis denotes the year.

Figure 4 Default Distribution with Time: Four States

A: Frequency Distribution of Default by Year



B: Percentage of Default by Year



Note: This figure shows the default frequency and percentage distribution of all kinds of loans by year for four states: California (CA), Florida (FL), Arizona (AZ), and Nevada (NV). In Panel A, the y-axis denotes the frequency of default loans, while x-axis denotes the year. In Panel B, the y-axis denotes the default rate, while X-axis denotes the year.

5. Empirical Results

5.1 Time Preferences and Mortgage Default

We use logistic regression to study the default behaviour of interest-only and 30-year adjustable-rate loans, relative to the 30-year fixed-rate loans. Table 3 reports the regression coefficients and odds ratios in the full sample analysis. Consistent with existing findings on the determinants of the default behaviour, owner-occupancy, lower LTV ratio, high FICO score, and lower loan balance predict a lower default rate in general. Besides, lower or no documentation loans are risky, and their default probabilities are higher. Column (1) shows the regression results of interest-only loans relative to the 30-year fixed-rate loans. It can be seen that 5-year interest-only loans are 36.8% more likely to be defaulted than 30-year fixed-rate loans after controlling for the other loan characteristics. The default probability for 10-year interest-only loans is 38.1% higher than that for 30-year fixed-rate loans, after controlling for other loan characteristics.

The results in Column (2) show the regression results for 30-year adjustable-rate loans relative to 30-year fixed-rate loans. The 30-year adjustable-rate loans are 34.7% more likely to be defaulted compared with the 30-year fixed-rate loans, after controlling for other loan characteristics. The last column shows the results in the full sample analysis, where the default probabilities for both interest-only and 30-year adjustable-rate loans relative to 30-year fixed-rate loans are presented. Compared with the 30-year fixed-rate loans, the default probability of 5-year interest-only loans is 32.3% higher, and that for 10-year interest-only loans is 32.3% higher. The 30-year adjustable-rate loans are 31.8% more likely to be defaulted relative to 30-year fixed-rate loans. Moreover, the default probability of 30-year adjustable-rate loans is lower than interest-only loans.

Table 4 presents the sub-sample default analysis in California, Florida, Arizona, and Nevada, respectively. As shown in Figures 2 and 4, the patterns of origination and default for each type of loan in these four states are similar to the full sample. Consistent with the results from the full sample, the average default rates for interest-only and 30-year adjustable-rate loans are higher relative to 30-year fixed-rate loans, and the default probability of 30-year adjustable-rate loans is lower than interest-only loans. In particular, borrowers of 5-year interest-only loans in California are 65.3% more likely to default than those who choose a 30-year fixed-rate loan, and 10-year interest-only loan borrowers are 60.2% more likely to default than those who selected the 30-year fixed-rate loans. On the other hand, 30-year adjustable-rate loan borrowers are 53.2% more likely to default than those who have selected 30-year fixed-rate loans in California.

Table 3 Time Preferences and Mortgage Default

Variable	IO VS FIX30	ARM30 VS FIX30	IO & ARM30 VS FIX30
IO5	0.313***		0.280***
	(0.003)		(0.002)
	[1.368]		[1.323]
IO10	0.323***		0.280***
	(0.003)		(0.003)
	[1.381]		[1.323]
ARM30		0.298***	0.276***
		(0.003)	(0.003)
		[1.347]	[1.318]
owneroc	-0.215***	-0.224***	-0.205***
	(0.003)	(0.002)	(0.002)
	[0.807]	[0.799]	[0.815]
low_no_doc	0.281***	0.205***	0.261***
	(0.003)	(0.002)	(0.002)
	[1.325]	[1.228]	[1.298]
subprime	0.367***	0.222***	0.274***
	(0.003)	(0.003)	(0.003)
	[1.444]	[1.248]	[1.316]
High LTV	1.181***	1.045***	1.138***
	(0.006)	(0.006)	(0.005)
	[3.257]	[2.843]	[3.120]
High fico	-1.201***	-1.041***	-1.106***
	(0.006)	(0.007)	(0.006)
	[0.301]	[0.353]	[0.331]
High Original Loan Balance	-0.194***	-0.096***	-0.096***
	(0.006)	(0.006)	(0.005)
	[0.824]	[0.909]	[0.909]
Log_MHPI	-0.481***	-0.402***	-0.455***
	(0.004)	(0.003)	(0.003)
	[0.618]	[0.669]	[0.635]
High duration	-0.410***	-0.118***	-0.101***
	(0.010)	(0.009)	(0.008)
	[0.663]	[0.888]	[0.904]
Observations	1,927,207	2,241,844	3,058,413
Pseudo R-Squared	0.6664	0.6243	0.6542

Notes: This table shows the results of a logistic regression analysis for the BlackBox dataset. The sample only includes 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. The dependant variable is "default", which takes the value of one for default loans and zero for others. *"High Ltv"* bucket contains loans with an LTV ratio higher than the mean value of the sample. *"High fico"* bucket contains loans with a FICO score higher than the mean value of the sample. *"High Original Loan Balance"* bucket contains loans with the amount of principal higher than the mean value of the sample. *"High duration"* bucket contains loans with a duration longer than the mean

value of the sample. The definitions of other independent variables are shown in Table 2. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and estimated odds ratios for the logit regression are reported in brackets.
*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Table 4 Time Preferences and Mortgage Default: Four States

Panel A: Logistic Regression: State of California (CA)

Variable	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.503***		0.455***
	(0.007)		(0.007)
	[1.653]		[1.576]
IO10	0.472***		0.428***
	(0.007)		(0.007)
	[1.602]		[1.535]
ARM30		0.427***	0.273***
		(0.008)	(0.007)
		[1.532]	[1.314]
Observations	437,487	322,103	573,012
Pseudo R-Squared	0.7841	0.7650	0.7919

Panel B: Logistic Regression: State of Florida (FL)

Variables	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.229***		0.177***
	(0.010)		(0.008)
	[1.257]		[1.193]
IO10	0.282***		0.205***
	(0.011)		(0.009)
	[1.326]		[1.227]
ARM30		0.252***	0.203***
		(0.010)	(0.010)
		[1.286]	[1.226]
Observations	171,346	191,050	266,849
Pseudo R-Squared	0.7809	0.7837	0.7859

Panel C: Logistic Regression: State of Arizona (AZ)

Variables	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.373***		0.334***
	(0.013)		(0.011)
	[1.451]		[1.397]
IO10	0.474***		0.410***
	(0.014)		(0.012)
	[1.606]		[1.507]
ARM30		0.343***	0.295***
		(0.015)	(0.013)
		[1.409]	[1.343]
Observations	128,980	110,668	187,854
Pseudo R-Squared	0.7907	0.7758	0.7900

Panel D: Logistic Regression: State of Nevada (NV)

Variables	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.319***		0.292***
	(0.019)		(0.017)
	[1.376]		[1.338]
IO10	0.440***		0.409***
	(0.019)		(0.018)
	[1.553]		[1.506]
ARM30		0.249***	0.211***
		(0.021)	(0.018)
		[1.283]	[1.234]
Observations	75,076	52,577	103,097
Pseudo R-Squared	0.8107	0.8038	0.8124

Notes: This table shows the results of a logistic regression analysis for four representative states, i.e., California, Florida, Arizona, and Nevada. The dependant variable is "default", which takes the value of one for default loans and zero for others. We do not report the entire list of control variables. Refer to Table 3 for the full lists. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and estimated odds ratios for the logit regression are reported in brackets.

*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Table 5 presents the sub-sample default analysis by setting the financial crisis as a breakpoint. Specifically, the sample is divided into two parts: loans that terminated before the financial crisis and loans that terminated after the financial crisis.[10] Generally speaking, for both before and after the financial crisis sample, all results are consistent with the results in the full sample. Before the financial crisis, 5-year interest-only loans were 9.8% more likely to be defaulted than the 30-year fixed-rate loans, after controlling for other loan characteristics. The default probability for 10-year interest-only loans is only 0.2% higher than that for 30-year fixed-rate loans, after controlling for other loan characteristics.

The results changed dramatically after the financial crisis. Those with a 5-year interest-only loan are 39.5% more likely to default than those with a 30-year fixed-rate loan, after controlling for other loan characteristics. The default probability of the 10-year interest-only loans is 42.1% higher than that of the 30-year fixed-rate loans. This divergence in the findings can be explained by the higher probability for back-loaded mortgages that minimize up-front costs to go "underwater" and default following negative home price shocks.

5.2 Robustness Analysis: Propensity Score Matching

The original loan size and other observable attributes of each type of loan are systematically different (see Table 1), and directly comparing their defaults might be misleading with an unbalanced sample. Therefore, PSM is used to obtain a more homogeneous sample for each comparison sample to mitigate the potential bias.[11] In particular, a one-to-one match for each treatment group based on the original loan balance, origination year, location of the property (at the MSA level), and other loan and borrower characteristics is performed.

Table 6 reports the summary statistics of the matched sample. Although PSM is not able to eliminate the differences in the loan and borrower characteristics of the interest-only and 30-year adjustable-rate loans relative to the 30-year fixed-rate loans, the gap between those observables is significantly reduced across these three types of loans after propensity matching. First, interest-only loans (the treatment group) are matched with 30-year fixed-rate loans (the control group) to mitigate the potential bias. In the matched sample, 22.44% of the loans are 5-year interest-only loans, and 27.56% are 10-year interest-only loans. The statistics of all of the variables are very similar after propensity matching for interest-only and 30-year fixed-rate loans. Second, the summary statistics are shown by matching 30-year adjustable-rate loans (the treatment group) with 30-year fixed-rate loans (the control group). Lastly, both interest-only and 30-year adjustable-rate loans (the treatment group) with 30-year fixed-rate loans

[10] For simplicity, the financial crisis is defined to commence at the start of 2009.
[11] The BBx dataset has fewer characteristics of the borrowers than the HMDA dataset. Therefore, the HMDA dataset is first matched with the BBx dataset to obtain more information about mortgage borrowers, including their race, sex, income, and homeownership status. Then propensity score matching is carried out based on the combined information from both datasets.

Table 5 Time Preferences and Mortgage Default: Financial Crisis Breakpoint

Panel A Terminated before Financial Crisis

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.094***		0.141***
	(0.009)		(0.006)
	[1.098]		[1.151]
IO10	0.002***		0.002***
	(0.009)		(0.007)
	[1.002]		[1.002]
ARM30		0.188***	0.186***
		(0.007)	(0.007)
		[1.207]	[1.204]
Observations	398,861	623,388	768,469
Pseudo R-Squared	0.1878	0.2386	0.2053

Panel B Terminated after Financial Crisis

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.333***		0.293***
	(0.003)		(0.002)
	[1.395]		[1.340]
IO10	0.351***		0.303***
	(0.003)		(0.003)
	[1.421]		[1.354]
ARM30		0.290***	0.255***
		(0.003)	(0.003)
		[1.337]	[1.290]
Observations	1,528,346	1,618,456	2,289,944
Pseudo R-Squared	0.6741	0.6420	0.6707

Notes: This table shows the results of a logistic regression analysis for the financial crisis breakpoint. For simplicity, the timeframe of the financial crisis is defined here as the beginning of 2009. Therefore, the two parts of the sample are: loans terminated before the end of 2008, and loans terminated after the beginning of 2009. The dependant variable is "default", which takes the value of one for default loans and zero for others. We do not report the entire list of control variables. Refer to Table 3 for the full lists. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and estimated odds ratios for the logit regression are reported in brackets.

*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Table 6 Summary Statistics of Variables: Propensity Score Matched Sample

Variables	IO. Loans Matched with FIX30			ARM30 Matched with FIX30			IO Loans and ARM30 Matched with FIX30		
	Matched total	IO. Loans	FIX30	Matched total	FIX30	ARM30	Matched total	IO loans and Arm30	FIX30
IO5	22.44%	44..88%					8.54%	17.08%	
IO10	27.56%	55.12%					13.54%	27.65%	
FIX30	50%		100%	50%	100%		50%		100%
ARM30				50%		100%	27.64%	55.28%	
Current Interest Rate	6.311	5.943	6.777	7.388	7.304	7.473	6.889	6.779	6.997
Original Loan Balance	253257.42	260233.81	246281.03	174980.54	173859.90	176101.17	205232.94	204689.88	205776.01
FICO Score	694.293	694.035	694.552	644.457	644.736	644.178	673.229	672.690	673.768
OrigLTVRatioCalc	77.304	77.356	77.253	81.168	81.239	80.980	78.672	78.561	78.768
Ownerocc	85.81%	85.85%	85.76%	88.33%	88.79%	87.86%	85.65%	85.38%	85.92%
low_no_doc	53.84%	53.88%	53.80%	37.70%	37.13%	38.26%	43.56%	43.21%	43.90%
Subprime	11.18%	11.35%	11.01%	34.20%	34.23%	34.17%	23.42%	23.98%	22.85%
Duration	58.259	55.896	60.621	58.063	62.828	53.299	31.361	55.893	62.829
LOG_MHPI	5.183	5.202	5.165	5.154	5.138	5.171	5.164	5.176	5.151
Sample size	625,444	312,722	312,722	671,158	335,579	335,579	1,008,224	504,112	504,112

Notes: This table presents the aggregate-level summary statistics of the BlackBox dataset after propensity score matching. The sample includes 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. Comparison of the average values of the variables by full sample, interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans are presented. The definitions of the variables are the same as those in Table 2.

(the control group) are matched. After propensity matching, 22.08% of the loans are interest-only loans, with 8.54% having a duration of 5-years and 13.54% being 10-years long, and 27.64% of the loans are 30-year adjustable-rate loans. In the treatment group, 44.72% of the loans are interest-only loans, with 17.08% being 5-year interest-only loans, 27.65% being 10-year interest-only loans, and 55.28% of the loans being 30-year adjustable-rate loans.

Table 7 presents the results of the logistic regression analysis on the default behaviour of interest-only and 30-year adjustable-rate loans relative to the 30-year fixed-rate loans in the matched sample. The findings are broadly consistent with those in Table 3: i.e., in the matched sample, the average default rate of interest-only and 30-year adjustable-rate loans is higher relative to that for 30-year fixed-rate loans, and the default probability for 30-year adjustable-rate loans is lower than that for interest-only loans.

Column (1) shows the regression results of interest-only loans relative to 30-year fixed-rate loans after propensity matching. It can be seen that default is more likely for 5-year interest-only loans than 30-year fixed-rate loans by 45.1% after controlling for other loan characteristics. Besides, the default probability of 10-year interest-only loans is 34.9% higher than that of 30-year fixed-rate loans after controlling for other loan characteristics. The results in Column (2) show that default is 22.4% more likely for 30-year adjustable-rate loans compared to 30-year fixed-rate loans, after controlling for other loan characteristics and propensity matching. The last column shows the results in the full sample analysis, where the default probabilities of both interest-only and 30-year adjustable-rate loans relative to those for 30-year fixed-rate loans are presented. Compared with the 30-year fixed-rate loans, the default probability of 5-year interest-only loans is 25.6% higher, and 20.8% higher for 10-year interest-only loans. The 30-year adjustable-rate loans are 21.5% more likely to be defaulted relative to the 30-year fixed-rate loans. Moreover, the default probability of 30-year adjustable-rate loans is lower than that of interest-only loans.

Table 8 presents the sub-sample default analysis on California, Arizona, Florida, and Nevada, respectively, in the propensity matched sample. The results are consistent with those in Table 4: the average default rates of interest-only and 30-year adjustable-rate loans are higher relative to the 30-year fixed-rate loans, and the default probability of 30-year adjustable-rate loans is lower than that for interest-only loans. The default probability of interest-only loans is particularly high in California. Borrowers of a 5-year interest-only loan in California are 63.6% more likely to default than those who select a 30-year fixed-rate loan, compared to borrowers of a 10-year interest-only loan who are 42.3% more likely to default than those with a 30-year fixed-rate loan.

Table 7 Time Preferences and Mortgage Default: Propensity Score Matched Sample

Variable	IO VS FIX30	ARM30 VS FIX30	IO & ARM30 VS FIX30
IO5	0.372***		0.228***
	(0.005)		(0.003)
	[1.451]		[1.256]
IO10	0.300***		0.189***
	(0.005)		(0.004)
	[1.349]		[1.208]
ARM30		0.202***	0.195***
		(0.004)	(0.004)
		[1.224]	[1.215]
ownerocc	-0.266***	-0.197***	-0.284***
	(0.005)	(0.004)	(0.004)
	[0.767]	[0.822]	[0.753]
low_no_doc	0.268***	0.188***	0.231***
	(0.005)	(0.004)	(0.004)
	[1.308]	[1.207]	[1.260]
subprime	0.300***	0.185***	0.313***
	(0.004)	(0.006)	(0.004)
	[1.350]	[1.203]	[1.368]
High LTV	0.220***	0.539***	1.089***
	(0.011)	(0.009)	(0.008)
	[3.385]	[1.714]	[2.970]
High fico	-1.241***	-0.748***	-1.180***
	(0.010)	(0.012)	(0.009)
	[0.289]	[0.474]	[0.307]
High Original Loan Balance	-0.131***	-0.018***	-0.116***
	(0.011)	(0.010)	(0.009)
	[0.877]	[0.982]	[0.891]
Log_MHPI	-0.491***	-0.421***	-0.474***
	(0.007)	(0.006)	(0.005)
	[0.612]	[0.656]	[0.623]
High duration	-0.2951***	-0.287***	-0.282***
	(0.018)	(0.016)	(0.013)
	[0.744]	[0.751]	[0.754]
Observations	625,444	671,158	1,008,224
Pseudo R-Squared	0.6645	0.6071	0.6201

Notes: This table shows the results of the logistic regression analysis for the BlackBox dataset after propensity score matching. The sample only includes 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. The dependant variable is "default", which takes the value of one for default loans and zero otherwise. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and the estimated odds ratios for the logit regression are reported in brackets.

*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Table 8 Time Preferences and Mortgage Default: Four States of Propensity Score Matched Sample

Panel A Logistic Regression: State of California (CA)

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.492***		0.411***
	(0.013)		(0.011)
	[1.636]		[1.508]
IO10	0.353***		0.289***
	(0.012)		(0.011)
	[1.423]		[1.336]
ARM30		0.194***	0.175***
		(0.015)	(0.012)
		[1.213]	[1.191]
Observations	120,666	89,928	156,870
Pseudo R-Squared	0.7441	0.7641	0.7334

Panel B Logistic Regression: State of Florida (FL)

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.241***		0.134***
	(0.018)		(0.013)
	[1.272]		[1.144]
IO10	0.265***		0.125***
	(0.018)		(0.133)
	[1.303]		[1.239]
ARM30		0.106***	0.128***
		(0.017)	(0.014)
		[1.112]	[1.136]
Observations	51,886	62,388	92,234
Pseudo R-Squared	0.7824	0.7908	0.7733

Panel C Logistic Regression: State of Arizona (AZ)

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.342***		0.230***
	(0.024)		(0.020)
	[1.407]		[1.259]
IO10	0.379***		0.250***
	(0.024)		(0.021)
	[1.461]		[1.284]
ARM30		0.148***	0.159***
		(0.025)	(0.023)
		[1.159]	[1.172]
Observations	34,012	29,700	43,448
Pseudo R-Squared	0.7681	0.7667	0.7495

Panel D Logistic Regression: State of Nevada (NV)

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.274***		0.207***
	(0.034)		(0.030)
	[1.315]		[1.230]
IO10	0.312***		0.218***
	(0.033)		(0.031)
	[1.366]		[1.244]
ARM30		0.112***	0.114***
		(0.038)	(0.032)
		[1.119]	[1.121]
Observations	16,732	13,234	19,452
Pseudo R-Squared	0.7963	0.8054	0.7947

Notes: This table shows the results of a logistic regression analysis for four representative states after propensity score matching, i.e., California, Florida, Arizona, and Nevada. The dependant variable is "default", which takes the value of one for default loans and zero for others. We do not report the entire list of control variables. Refer to Table 3 for the full lists. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and the estimated odds ratios for the logit regression are reported in brackets.

*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Table 9 presents the sub-sample default analysis by setting the financial crisis as a breakpoint in the propensity matched sample. The results are consistent with those shown in Table 5: the default probabilities of both interest-only and 30-year adjustable-rate loans are higher than that of 30-year fixed-rate loans. However, there is substantial difference between the results before and after the financial crisis. Before the financial crisis, borrowers of a 5-year interest-only loan are approximately 14.7% more likely to default than those who select a 30-year fixed-rate loan. After the financial crisis, borrowers of a 5-year interest-only loan are around 45.7% more likely to default than those who select a 30-year fixed-rate loan. In comparison, borrowers of a 10-year interest-only loan are only around 37.2% more likely to default than those who select a 30-year fixed-rate loan. The results for the 30-year adjustable-rate loans relative to 30-year fixed-rate loans are similar.

Table 9 Time Preferences and Mortgage Default: Financial Crisis Breakpoint of Propensity Score Matched Sample

Panel A: Terminated before Financial Crisis

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.137***		0.039***
	(0.018)		(0.012)
	[1.147]		[1.040]
IO10	-0.014		-0.107
	(0.019)		(0.014)
	[0.986]		[0.898]
ARM30		0.084***	0.060***
		(0.012)	(0.012)
		[1.088]	[1.062]
Observations	96,862	167,070	203,072
Pseudo R-Squared	0.1531	0.2357	0.2319

Panel B Terminated after Financial Crisis

	IO VS FIX30	ARM30 VS FIX30	ARM30 & IO VS FIX30
IO5	0.377***		0.251***
	(0.005)		(0.004)
	[1.457]		[1.286]
IO10	0.316***		0.220***
	(0.005)		(0.004)
	[1.372]		[1.246]
ARM30		0.211***	0.199***
		(0.005)	(0.004)
		[1.234]	[1.220]
Observations	512,398	492,250	789,000
Pseudo R-Squared	0.6750	0.6209	0.6372

Notes: This table shows the results of the logistic regression analysis for financial crisis breakpoint after propensity score matching. For simplicity, the timeframe of the financial crisis is defined here as the beginning of 2009. Therefore, the two parts of the sample are: loans terminated before the end of 2008, and loans terminated after the beginning of 2009. The dependant variable is "default", which takes the value of one for default loans and zero for others. We do not report the entire list of control variables. Refer to Table 3 for the full lists. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and estimated odds ratios for the logit regression are reported in brackets.

*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

5.3 Loans that Originated between 2004 and 2007

The subprime mortgage market snowballed between 2001 and 2007. Kiff and Mills (2007), among others, argue that this was facilitated by the development of private-label mortgage-backed securities, which do not carry the kind of credit risk protection offered by government-sponsored enterprises. Demyanyk and Hemert (2011) analyze loans that originated between 2001 and 2006 and find that, during the dramatic growth of the subprime (securitized) mortgage market, the quality of the market deteriorated dramatically. Besides, significant changes to Regulation C, which implemented the HMDA, took effect in January 2004. These changes, designed primarily to enhance the understanding of mortgage markets and assist in fair lending enforcement, increased the amount and types of public information about residential real estate lending. Due to the dramatic growth of loans and new regulations, a sub-sample that consists of mortgages that originated between 2004 and 2007 is created and the same regressions are run as in Tables 3 and 6.[1] The results are consistent with our findings in the previous sections.

Table 10 Time Preferences and Mortgage Default: Loans Originated between 2004 and 2007

	Original Sample		
Variable	IO VS FIX30	ARM30 VS FIX30	IO & ARM30 VS FIX30
IO5	0.328***		0.286***
	(0.003)		(0.002)
	[1.388]		[1.332]
IO10	0.327***		0.277***
	(0.003)		(0.003)
	[1.386]		[1.319]
ARM30		0.301***	0.267***
		(0.003)	(0.003)
		[1.351]	[1.305]
Observations	1,567,667	1,654,772	2,447,692
Pseudo R-Squared	0.6667	0.6203	0.6524

(***Continued…***)

[1] A sub-sample analysis of loans that originated between 2004 and 2007 for the four states and the financial crisis breakpoint is also done, but the results are not reported in the paper. The results are consistent with our previous results.

(Table 10 Continued)

	Matched Sample		
Variable	IO VS FIX30	ARM30 VS FIX30	IO & ARM30 VS FIX30
IO5	0.341***		0.232***
	(0.005)		(0.004)
	[1.407]		[1.261]
IO10	0.287***		0.205***
	(0.005)		(0.004)
	[1.332]		[1.228]
ARM30		0.196***	0.186***
		(0.005)	(0.004)
		[1.217]	[1.204]
Observations	571,868	504,368	770,614
Pseudo R-Squared	0.6596	0.6031	0.6255

Notes: This table shows the results of the logistic regression analysis for the BlackBox dataset with loans that originated between 2004 and 2007: both before and after propensity score matching. The sample only includes 5-year and 10-year interest-only loans, 30-year fixed-rate loans, and 30-year adjustable-rate loans. The dependant variable is "default", which takes the value of one for default loans and zero for others. State, current year, and origination year fixed effects are included in the regression but not reported. Standard errors are reported in parentheses, and the estimated odds ratios for the logit regression are reported in brackets.
*Significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

6. Conclusion

The ongoing recession and surging rate of unemployment caused by the COVID-19 pandemic might trigger a crisis of mortgage defaults. The large number of mortgage defaults and different default behaviours have led us to think more deeply about the theory and practice of residential mortgage defaults and foreclosures. Mortgage default behaviours are complex. Correctly identifying the different types of default behaviours of borrowers is not only important for mortgage lenders and investors of mortgage-backed securities but also crucial for policymakers.

This paper investigates whether heterogeneity in the time preferences of borrowers, as manifested in their mortgage choices, correlates with their decision to default. Our findings suggest that present-biased borrowers who select back-loaded mortgages are more likely to default than dynamically consistent borrowers. In particular, naïve borrowers with present-biased preferences, who are more likely to choose interest-only loans, default earlier than borrowers of other types of loans. If borrowers have present-biased preferences or suffer from short-term temptations and are aware of the consequences (termed as “sophisticated” as opposed to “naïve”), then it is likely they will prefer to refrain from temptation and behave more rationally. For dynamically-consistent borrowers, the choice of fixed-rate loans leads them to default less frequently than others. The relationship between present bias and mortgage default is maintained when controlling for the demographics and loan characteristics of the borrowers.

Overall, the heterogeneous time preferences of borrowers as evidenced in their choice of type of mortgage, may help to improve our understanding of mortgage default behaviour. They will also contribute to facilitating better policies to manage foreclosure crises, such as for mortgage modifications and mortgage contract designs.

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