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Dynamic Analysis of Defaults and Prepayments in the Turkish Mortgage Market

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Türkiye Mortgage Piyasasındaki Temerrütlerin ve Erken Ödemelerin Dinamik Analizi

Abstract

We analyze the determinants of default and prepayment in the Turkish mortgage market by utilizing data obtained from a large commercial bank. Our main findings suggest that default is positively affected by a high loan to value ratio and term length of mortgages, and negatively affected by certain quantitative easing periods, good expectations regarding the future, the ratio of real house prices to the size of the economy and mortgage customer’s high school and above level of education and being married. The probability of prepayment rises with the increase in variables such as the gain ratio due to prepayment, high school and above level of education of the mortgage customer, size of the GDP and the ratio of real house prices to GDP. We also find that the likelihoods of both the cases of default and prepayment are locally maximized when nearly 60% of the term is reached.

Keywords : Mortgage, Default, Prepayment, Dynamic Analysis, Logistic Regression.

JEL Classification Codes : C33, E44, G21.

Öz

Bu çalışmada, Türkiye mortgage piyasasındaki temerrüt ve erken ödemelerin belirleyicileri, ticari bir bankadan temin edilen veriler kullanılarak, analiz edilmektedir. Temel bulgularımız göstermektedir ki; borç-değer rasyosunun ve mortgage kredisi vadesinin yükselmesi temerrüt olasılığını arttırıcı etkide bulunmaktayken, bu olasılığı azaltıcı temel etkenler ise bazı parasal genişleme dönemleri, geleceğe dair iyi beklentiler, reel konut fiyatlarının ekonomik büyüklüğe oranı ve mortgage kredisi müşterisinin lise ve üstü eğitim seviyesine sahip ve evli olmasıdır. Erken ödeme olasılığı ise erken ödemeden kaynaklı kazanç oranı, mortgage müşterisinin lise ve üstü eğitim düzeyi, GSYH büyüklüğü ve reel konut fiyatlarının GSYH’ye oranı değişkenlerindeki artış ile yükselmektedir. Makalede ayrıca, vadenin yaklaşık %60’ına ulaşıldığında hem temerrüt hem de erken ödeme olasılıklarının en üst düzeye çıktığı bulunmuştur.

Anahtar Sözcükler : Mortgage Kredisi, Temerrüt, Erken Ödeme, Dinamik Analiz, Lojistik Regresyon.

1. Introduction

The question of what drives prepayment and default behaviours of mortgage customers has remained significant to comprehend the structure of financial markets and household attitudes. Without any consumer debt, many household or people could not afford to own a house. Therefore, mortgage loans have potential to offer customers the opportunity to purchase house by managing their regular income well. Rationally, to ensure long-term life cycle, transfer from future resources to pay for current consumption, customers and financial intermediaries must appropriately manage their borrowings (debts) and lending (loans) operations. Excessive debt or easy lending might result in economic and social frustration. There are also links between the markets for consumption goods and housing that directly affects liquidity considerations for mortgage markets.

Mortgage contracts cover some significant characteristics; interest rates, maturity, housing price, income et al. Besides these factors, mortgage contracts or debts might also influence social aspects of households such as marriage satisfaction. For instance, according to the National Survey of Families and Households data from USA, any dramatic change in consumer loan debt can predict changes in marital satisfaction of couples (Xiao, 2015). This issue has also been related with customer culture and might vary across countries. Hence, country based empirical studies, like ours, might shed light on country or cultural differences.

On the mortgage creditors side, the main question, perhaps the most significant, is how to handle or identify potential defaulters. It can be also claimed that mortgage or loan issuers have less incentive or signals to identify possible defaulters in a way related to lending standards. A loose filtering process or lender-friendly loan evaluation procedure might increase the number of defaulters whereas a strict filtering process might narrow mortgage demand.

The probability of default and prepayments might appear to be influenced by different set of customer and macroeconomic specific factors such as marriage status, income level, occupation, age, lenght of mortgage contract term, housing prices, interest rates, income shocks et al. (LaCour-Little, 2008; Doviak & MacDonald, 2012). In general, studies focusing on default and prepayment behaviors use three known variables in their regression analyses: loan to value (LTV), loan to income (LTI) and mortgage payment to income (MTI) ratios. It is also a known fact that wage-indexed mortgage payment might better protect borrowers compared to the nominal mortgage contractor (Campbell & Cocco, 2012). Many other variables can be added to either list depending on other conditions. Another important point related to default or prepayment attitudes is whether it was made strategically or out of necessity. Sometimes borrowers may strategically choose not to repay debts, even if they can afford to do so, which is called as strategic default since borrowers use complex contracts as strategically and choose to default whenever it is profitable (Wyman, 2010). Based on literature review, we examine and interpret our analysis into two categories: Defaults and prepayments.

In our case, there are no studies examining the conditional probabilities and determinants of defaults and prepayments on mortgage contracts in Turkey. Some quantitative and qualitative models focusing on customer history, income, credit scoring and occupation can not provide sufficient and required information. The present empirical research is a step to fill this gap and the Turkish commercial banks may benefit by integrating these results with their internal default predictions or credit-risk scoring.

In this context, by using the data from large commercial private bank Garanti, we attempt to analyse the determinants of defaults and prepayments in the Turkish mortgage market which has experienced a rapid expansion over last decade. We use data from a large commercial bank's mortgage contracts that were introduced on March 2007 in Turkey and quickly replaced with regular housing credits. The individual level mortgage data covers the period between June 2007 and January 2014. Briefly and generally, we find that the probability of default rises with the loan to value ratio and it is less likely for a borrower to default at the initial and final months of payment. In other words, the likelihood of default is locally maximized when 62% of the term (74th month for a 120-month contract) is reached. The term length of the contract, expectations about house prices and education affect the probability of default.

This empirical paper proceeds as follows: The next section reviews the literature on defaults and prepayments behaviours. We present the data and model in section 3. We discuss the empirical methodology in section 4 and the estimation results in section 5. The last section concludes the paper.

2. Literaure Review

Multiple studies examine the factors behind default and prepayment attitudes. The literature can be grouped based on several categorizations. It can be classified based on whether the focus is on defaults or prepayments. An alternative categorization can be made based on how much control the borrower has over default and prepayment decisions, i.e. depending on whether the decision was made strategically or out of necessity. Opportunities would be presented by the changing market conditions, interest rates, real house prices, macroeconomic conditions and international dynamics. Constraints are imposed by household income, marriage, age, unemployment, house equity, loan-to-value ratio. Many other variables can be added to either list depending on other conditions. These two categories need not be mutually exclusive; often variables pertaining to both explanations would be included in regressions. It is the relative emphasis put on them that merits categorization. Our study represents the first of the kind for the Turkish market. Therefore, it inevitably maintains an exploratory nature while performing formal causal analyses.

For instance, LaCour-Little (2008) presents theoretical and empirical evidence on mortgage defaults, specifically focusing on termination risks that are directly linked to economic factors. Besides the economic factors, Wyman (2010) and Guiso and Sodini (2012) differentiate between strategic default and economic default. According to them, some borrowers strategically choose to discontinue payments despite being able to afford them. This is called strategic default. In our Turkish mortgage case, we do not differentiate between economic and strategic default.

The effect of loan restructuring on default and prepayment are observed by a number of studies. The fact that wealth motives tend to be an important determinant of default decisions at high levels of negative equity is consistent with the empirical findings of Haughwout et al. (2016). They find that the re-default rate declines relatively more when payment reduction is achieved through principal forgiveness as compared to lower interest rates. The empirical analysis of Doviak and MacDonald (2012) also emphasizes the role of modifications that reduce loan balances in preventing default. Mortgage refinancing is shown by Chen et al. (2013) to play an important role in consumption smoothing, suggesting there are links within the market for consumption goods and housing. Elul et al. (2010) provides empirical evidence on the importance of liquidity considerations for mortgage default decisions.

Regarding country analyses, most studies examine the US and UK markets since these countries have financial deepening mortgage markets and any extra default risk regarding the mortgage market triggers the crisis scenarios. For example, Mian and Sufi (2009) studies the sharp increase in mortgage defaults in the US market before the 2008 financial crisis. Based on mortgage level ZIP code analyses, they find that mortgage credit expansion rapidly grew between 2002 and 2005 despite sharply declining relative to income growth. In other words, income and mortgage credit growth move into opposite directions. Using data from US States, Ghent and Kudlyak (2011) analyse default behaviours of mortgage lenders and show that borrowers are 30% more likely to default in non-recourse states. They reveal that lender-friendly loan evaluation procedures increase the probability of default.

There are very few studies examining default and prepayment behaviours in emerging economies and Turkey. In most of studies on mortgage defaults, three main variables are used. First is the loan to value (LTV) ratio where loan is the total amount of borrowing used in financing the property and value represents its concurrent market price. The second is the loan to income (LTI) ratio where income is a measure of household earnings for a period, usually year or month. The third is the mortgage payment to income (MTI) ratio where the mortgage payment refers to the periodic deposit made to the bank toward the mortgage loan and income is the household earnings within the same period. For instance, Erol and Patel (2005) uses wage-indexed payment mortgage data and finds that wage-indexed mortgage payment protects the borrower while nominal mortgage contracts might result in higher mortgage default in Turkey.

Ambrose and Sanders (2003) do not find any relationship between default/prepayment and LTV. Schwartz and Torous (2003) have found that the age of the mortgage plays an important role in regressions aimed at explaining default rates. Kang and Zenios (1992) use basis functions to capture the complex interactions between interest rate differentials and prepayment rates in their calibrations. Kalotay et al. (2004) argue that the market value of a mortgage should be emphasized rather than future payments. Navratil

(1985) uses the difference between the prevailing market rate and the contract rate. The relationship is most elastic when the current market rate is 300 basis points below the current market rate. Bajari et al. (2008) emphasize the role of house price declines and deterioration in loan quality.

Deng et al. (2000) suggests that the borrowing agent would exercise the option in the form of a mortgage default if it is in the money where the main determinant is the property value. However, the agent would not do this immediately after facing negative home equity since property prices may increase in the future. The difference between property value and the outstanding loan balance is termed as house equity. A decreasing and eventually negative house equity is considered among the main determinants of mortgage defaults in the literature. This variable was also addressed in papers predating the crisis, such as Vandell (1978) and Campbell and Dietrich (1983).

More recent research such as Campbell and Cocco (2012) emphasizes additional variables and specifications that determined the mortgage decision. According to their model, house equity has a triggering effect, however the threshold level for this effect depends on the borrowing constraints and other shocks faced by the household in variables such as income and inflation. Following the same reasoning, they conclude that the effect of these variables would be different for fixed rate mortgage (FRM) and adjustable rate mortgage (ARM) contracts. In the case of an ARM contract, an interest rate shock would incentivize an agent to default through an increase in borrowing constraints. A high initial LTV ratio would make mortgage default more likely since the probability of having low and negative home equity would have been increased. The effect of the initial LTV is empirically supported by the findings of Mayer et al. (2009) and Schwartz and Torous (2003). However, there are also studies arguing that a negative property value does not always translate into a default decision. Foote et al. (2008) observe that the rate of default is below 10% for homeowners in Massachusetts, U.S. among those experiencing negative house equity. Quigley and Order (1990) test the option models for prepayments and find that the extent of the prepayment option being in the money has a strong effect, but it is not exercised as ruthlessly as the theory predicts.

3. Methodology

Analysis of events such as volcano explosions, wars, cancer etc. is important yet hard to be perform since such events occur very rarely. That is, we have generally a tiny proportion of these events (ones in binary data) in the data set than nonevents (zeros). Early termination events such as default and prepayment can also be categorized in this group.

Our sample has also very few observations of default and prepayment to qualify these two cases as rare events. They become further rare when the panel conversion is applied.

This is shown to create biases and inconsistencies for limited dependent variable regressions. Specifically, in probability models, namely logit, serious problems arise due to the fact that maximum likelihood estimation of the logistic model suffers from small-sample bias. Here the degree of bias is strongly dependent on the number of cases in the rarer events of the two categories of the dependent variable.

To address this problem, King and Zeng (2001) introduce an adapted version of the logistic regression, named rare events logistic regression. This algorithm mainly utilizes the method developed by It is essentially a logit regression where all observation on the rare cases are coupled with a sample drawn from the non-rare one. The results are unbiased and consistent in large samples.

In their approach, King and Zeng (2001) apply a number of corrections. They firstly suggest employing a case-control sampling design using stratified sampling. That is, they recommend a random selection of zeros in binary data. Now, the coefficients of explanatory variables are approximately unbiased, whereas the constant term may be significantly biased. Then, to account this bias, the prior correction method adjusts the constant term. The corrected intercept coefficient is:

$$\beta_0 = \hat{\beta}_0 - ln\left[\left(\frac{1-\tau}{\tau}\right)\left(\frac{\bar{y}}{1-\bar{y}}\right)\right]$$

where $\hat{\beta}_0$ is uncorrected intercept coefficient, while τ and $\bar{y}$ are the fraction of ones in the population and the observed fraction of ones in the sample (or sampling probability) respectively.

The slope coefficients are also biased in the sample of rare events data and are corrected via:

$$\tilde{\beta} = \hat{\beta} - bias(\hat{\beta})$$

where $\hat{\beta}$ refers to the maximum likelihood estimator. So $\tilde{\beta}$ denotes the corrected slope coefficients. Here the bias in $\hat{\beta}$ can be estimated by the following weighted least-squares expression:

$$bias(\hat{\beta}) = (X'\mathrm{W}X)^{-1}X'\mathrm{W}\xi$$

where $\xi_i = 0.5Q_{ii}[(1 + w_1)\hat{\pi}_i - w_1]$, Q_{ii} are the diagonal elements of $Q = X(X'\mathrm{W}X)^{-1}X'$, and $\mathrm{W} = diag\{\hat{\pi}_i(1 - \hat{\pi}_i)w_i\}$. Here $\hat{\pi}_i$ denotes the probability of $\Pr(Y_i = 1 \mid \hat{\beta})$ and $w_i = w_1Y_i + w_0(1 - Y_i)$ in which $w_1 = \tau/\bar{y}$ and $w_0 = (1 - \tau)/(1 - \bar{y})$.

Then, the outcome we are looking for is to estimate $\pi = \Pr(Y_i = 1 \mid \beta)$. To do this estimation we employ $\tilde{\pi}_i = \Pr(Y_i = 1 \mid \tilde{\beta}) = \frac{1}{1+ e^{-x_i\tilde{\beta}}}$ where x_i is a vector which includes a constant and explanatory variables that will be explained in the following section.

In this study, we employ the approach of King and Zeng (2001) and their STATA software package, named “relogit”, developed for the estimation correction model mentioned above. Here we apply relogit package with the assumption that early termination choices of credit borrowers are rare events, thus the term "event" corresponds to an occurrence of default or prepayment. We compare and verify the results against the standard logit regressions as robustness check and support the propositions of King and Zeng (2001).

4. Data

In the housing market, having real data is very hard to be obtained especially for the data of credits. In the absence of surveys, the only reliable source of individual level data is the bank records. The data used in this study is obtained from a large commercial bank operating in all regions of Turkey, Garanti Bank. Our dataset covers all mortgage credits given by this bank after the introduction of the new legislation June 2007 up to January 2014.

The data consists of basic information for the credits, namely amount, term, interest rate of credit and value of the house, and descriptions for the borrower as follows: income[1], age, marital status and education level. Information of date and amount for both default and prepayment events in a given borrower are also provided.

The entries are created at the opening of the credit and updated only if refinancing option is chosen by the borrower. Hence the dataset is of static nature. Information regarding income levels and demographics are obtained as a snapshot of the customer base. This results in a mismatch between the income level and marital status variables between the two datasets since they are recorded at different points in time. This problem is addressed by using marital status change dates and wage indices to correct or approximate the relevant entries.

Our focus is on the dynamic probabilities of default and prepayment therefore the dataset as obtained has little utility for our purposes. To run panel regressions, the dataset had to be converted into a panel format. That is, we must convert the data from static to dynamic form. We achieve this by taking the initial credit information along with the corrected and approximated additions then calculating a series of new variables. For each period, the outstanding loan balance (OLB) is calculated. OLB is then used to calculate the loan-to-value ratio in period t. Most variables other than demographics are based on these two variables.

The data of credit structure, demographics and key macroeconomic fundamentals which we employ as the determinants of early termination events of credit borrowers in a given bank are composed of the following variables:

"Defaulted" and "Prepaid" are dummy variables that register one if the borrower defaults or prepays respectively in the current period and zero otherwise. "LTV" stands for loan to value ratio and is calculated by dividing the credit amount to the value of the house.

[1] *When we were cleaning the data, we found that the income data could not collected very well, so we dropped it out from the regression analysis. However, we give basic descriptives of the data to provide an opinion about it.*

“Prepayment Gain Ratio” is the differential between the total amounts that would be paid when the term is completed normally or with a prepayment. It measures how much the borrower has to gain from prepayment. “Age of Term” is calculated by dividing the number of the current month by the number of total months. Its main role is to test whether borrowers are equally likely to default or prepay throughout the term or if they are less likely to default in the beginning and towards the end. “Term” stands for the number of months the payments will be made to the bank to honor the credit.

“Age of Customer” is the age of the borrower in the current period. “Education2”, “Education3”, “Education4” dummies stand for middle-high school, undergraduate and graduate education levels, respectively. “Married” dummy variable controls for the marital status with 1 corresponding to be married. “Term Medium” and “Term Long” are dummies corresponding to terms of lengths shorter than 60 months, between 60 and 120 months, and longer than 120 months, respectively.

“QE1”, “QE2”, “QE3” are dummy variables that capture the effect of three different quantitative easing periods by the Federal Reserve in the U.S. and capture the effect of global dynamics. The same goes for “Operation Twist”. The variable of “General Expectations” is a catch-all index published by the Central Bank of Turkey to reflect the economical expectations regarding near future. “Normalized Real GDP and “Real House Price over GDP” are self-explanatory. Real house price component of the latter variable is calculated by dividing the Reidin real house price index by the real GDP. “Real FX Rate” is the real rate of U.S. dollar to Turkish lira. “Real Mortgage Rate” is the average real mortgage credit rate in the market in the current period.

4.1. Data Description

In this study, we use credits data which is obtained from a large commercial bank operating in all regions of Turkey. This dataset consists of all mortgage credits given by this bank from June 2007 to January 2014. As far as we know, this is the biggest dataset used to understand Turkish housing credit market. Detailed data descriptions and their sources can be found in Table 1.

Table: 1
Data Descriptions and Sources

Data	**Description**	**Frequency (or Basis)**	**Source**
Credit	Total amount of mortgage loan in TL	Account Basis	Garanti Bank
House Price	Value of house subject to given credit in TL	Account Basis	Garanti Bank
Term	Number of months the payments will be made	Account Basis	Garanti Bank
Mortgage Rate	Interest rate subject to given credit at the begining in %	Account Basis	Garanti Bank
Income	Amount of monthly income of mortgage customer in TL	Account Basis	Garanti Bank
Age	Age information of mortgage customer	Account Basis	Garanti Bank
Education	Education level categorization of mortgage customer	Account Basis	Garanti Bank
Marital Status	Marital Status of mortgage customer	Account Basis	Garanti Bank
QEs	Dummy variables capturing the quantitative easing periods by the Federal Reserve in the U.S.	Monthly	FED
General Expectations	Catch-all index reflecting economical expectations regarding near future	Monthly	CBRT
GDP	Gross Domestic Product of Turkey	Quarterly	TurkStat
HP Index	House Price Index	Monthly	Reidin
Real FX Rate	Real rate of U.S. dollar to Turkish lira	Monthly	CBRT
Mortgage Interes Rate	Average mortgage credit rate in the market	Monthly	CBRT

Additionally, basic descriptives for the variables used in our analyses in this study are illustrated in Table 2. Original data consists of both credit specific and demographic variables. For 186880 mortgage accounts average credit amount is 78,356 TL while average LTV ratio is 59% and term is 86 months. Monthly mortgage rate has an avarage of 0.9%. Most prominent feature in credit variables is that income and house price have higher standard deviations regarding mean values. Looking at the demographic variables, we can see that average of mortgage customers’ age is 39, while their education level is averaged on high school degree. Finally, the table illustrates that 86% of mortgage customers are married.

Table 2 also provides information about descriptives of both defaulted and prepaid customers. Compare to non-defaulted mortgage customers, defaulted ones have more credit amount, loan to value ratio and mortgage rate. It also seems that the average income level of defaulted customers is double and average value of their house subject to mortgage is higher in comparison with other customers. Additional distinctive feature of defaulted mortgage owners is that they have lower education level and mariage percentage in average, while their age level is slightly higher. When we look at the default specific variables, we can see that average period of defaulted credits is the 20th month and the defaulted amount to house price ratio is nearly 0.5.

Table: 2
Summary of Descriptive Statistics

Category	Variable Group	Variable	# of observations	Mean	Standard Deviation	Minimum	Maximum
All	Credit Variables	Credit	186880	78355.88	69641.4	8000	5500000
		LTV	186880	0.592	0.160	0.012	0.799
		Term	186880	85.679	34.388	1	249
		Mortgage Rate	186880	0.008	0.001	0.000	0.018
		Income	186880	4436.463	94799.39	500	3.100
		House Price	186880	139669.2	139319.6	20000	1.100
	Demographic Variables	Age	186880	38.542	9.970	16	81
		Education	186880	4.330	1.394	0	8
		Married	186880	0.858	0.348	0	1
Defaulted	Credit Variables	Credit	355	95680.86	101696.9	13645	1100000
		LTV	355	0.663	0.125	0.023	0.797
		Term	355	85.157	35.822	4	240
		Mortage Rate	355	0.009	0.001	0.005	0.015
		Income	355	9961.346	79730.65	656	1500000
		House Price	355	150169.6	177583.9	26000	1800000
	Demographic Variables	Age	355	39.256	8.785	21	64
		Education	355	4.011	1.246	2	7
		Married	355	0.783	0.412	0	1
	Default Specific Variables	Defaulted Period	355	20.363	8.898	4	41
		Defaulted Amount	355	77425.52	79535.15	1386.97	797595.1
Prepaid	Credit Variables	Credit	18157	80580.32	83130.05	10000	2600000
		LTV	18157	0.579	0.164	0.062	0.799
		Term	18157	73.272	32.678	5	240
		Mortgage Rate	18157	0.009	0.001	0.002	0.018
		Income	18157	4566.2	8486.72	500	503000
		House Price	18157	144109.9	155275.4	20000	5382000
	Demographic Variables	Age	18157	39.801	9.423	19	79
		Education	18157	4.554	1.409	0	8
		Married	18157	0.859	0.347	0	1
	Prepayment Specific Variables	Prepaid Period	18157	23.359	10.913	1	77
		Prepaid Amount	18157	54330	64456.02	899.37	2173269

Prepaid customers' differences compared to others in term of average levels can also be seen in the table. The values in the table illustrate that prepaid customers' average levels of credit amount, mortgage rate, income and value of the house become higher, but the LTV ratio becomes shorter in comparison with other customers. Furthermore, average values of all demogaphic descriptives of customers using prepayment option are barely higher than others. We can also reach that the average period of prepayment is beyond 3 months compared to the default situtation. Finally, the prepaid amount is nearly two thirds of the defaulted amount and 40% of house value is subject to credit used by prepaid customers.

5. Results

The results are grouped in under default and prepayment categories based on the dependent variable. The results of rare events logistic regression analysis for the default and prepayment cases can be seen in Table 3 and 4 respectively. To interpret the coefficients in these tables, Table 5 provides the probability changes in level and return for initial analyses of both the default and prepayment cases. Firstly, the probability of default part will be examined.

5.1. Probability of Default

The initial regression in Table 3 controls for the real FX rate (USD/TRY). Probability of default increases with the LTV. This is an expected result and consistent with the literature. Borrowers who have high loan to value ratio are more likely to experience difficulties in mortgage payments compared to a low loan to value ratio since higher LTV expresses that mortgage borrowers have less down payment and high debt (loan) burden. According to Table 5, based on our initial default regression model results, about 10% rise in the mean value of LTV ratio causes the probability of default to increase by 1.195%.

The age of the mortgage contract has an effect: it is less likely for a borrower to default at the initial and final months of payment. The likelihood of default is locally maximized when 62% of the term is reached, e.g. probability of default is maximized on the 74th month for a 120-month contract. This is an important finding in the sense that it gives valuable signals to mortgage creditors about the timing of default risk.

Only the second quantitative easing dummy has a significant effect. The default probability was lowered by the second quantitative easing. Operational twist on the other hand has a larger negative effect with a better p-value. The age of the borrower increases the probability of default in a concave manner where it peaks at about 41 years, then drops. Education does not have a significant effect unless the borrower attended high school and above. More educated borrowers have a lower chance of default. The length of term affects default probability. Long term credits have a positive effect on default whereas middle term credits have a negative effect on default. Better expectations about the future reduces the probability of default. This result is also consistent with the strategic default literature in which borrowers strategically choose to not pay when he or she realizes that the real housing price will fall.

Additionally, the ratio of real house prices to GDP has a negative effect, implying that default is less likely if the real value of houses is growing faster than the economy.

The second regression in Table 3 eliminates the FX rate from the equation and reruns it. When the real FX rate is excluded QE3 and normalized GDP gain significance. In other words, they are not significant when the FX rate is controlled for. This is not surprising, given the sensitivity of the real FX rate in Turkey to FED decisions and how dependent GDP is on it. There are no sign changes between the results with and without the real FX rate.

We divide the sample in two, based on whether the observation is made during or after the crisis. Surprisingly, the intercept term loses statistical significance. The magnitude of the age and age-squared terms remain the same, but their p-values change, probably due to the lowered sample size.

Being married also significantly reduces the probability of default. Based on our initial results, married mortgage borrowers have about 1% lower likelihood of default compared to single borrowers.

Dividing the sample in two based on the initial LTV ratio shows that credits with a high LTV ratio are more sensitive to the real house price over GDP variable. The effects of LTV and age terms are not statistically significant when initial LTV is low.

Finally, dividing the sample based on credit amount suggests that the intercept is not significant for the medium and large-scale credits. The magnitude of the intercept is higher for the small-scale credits. This signals that small-scale credits have an exceptionally high default rate to begin with. Age terms lose significance in the small and large-scale credit cases.

5.2. Probability of Prepayment

Our regression analysis about prepayment can be seen in Table 4. The age of mortgage has a concave effect on prepayment probability. The maximum effect is observed when the 60% of the term is passed. QE1 and QE3 are significant whereas QE2 is not. This is completely the inverse of the case of default. The first and the third quantitative easing periods affected the probability of prepayment whereas the second one did the same for defaults. The first easing resulted in an increase in prepayments whereas the third one in a decrease. The magnitudes are offsetting each other, suggesting that the end outcome from the perspective of the banks was neutralized. Operational twist had a negative effect on prepayment probability as it did on default probability. Better expectations of future economic conditions have a positive effect on prepayments so does the size of real GDP and real house prices over GDP.

Table: 3
Rare Events Logistic Regressions for the Case of Default

	Initial Analysis		**Crisis Effect**		**Initial LTV Ratio**		**Credit Amount**		
	FX Controlled	FX Eleminated	During Crisis	After Crisis	Low LTV Ratio	High LTV Ratio	Small Scale	Medium Scale	Large Scale
Constant	6.43*	7.24*	4.12	4.77	13.56*	8.71*	11.59*	5.06	10.34
	(0.08)	(0.06)	(0.41)	(0.49)	(0.08)	(0.06)	(0.09)	(0.37)	(0.22)
LTV	3.52***	3.51***	2.27***	6.54***	1.12	2.06***	3.43***	2.80***	2.66***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.55)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Term	8.45***	8.52***	6.78***	13.66***	9.31***	7.96***	8.02***	8.95***	8.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Term - Squared	-6.80***	-6.86***	-4.56***	-10.19***	-7.21***	-6.91***	-5.67***	-7.55***	-7.21***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Normalized Real GDP	-0.03	-0.05*	-0.04	0.06	-0.10**	-0.05	-0.08	-0.03	-0.08
	(0.48)	(0.07)	(0.27)	(0.48)	(0.05)	(0.18)	(0.11)	(0.50)	(0.22)
Real HP over GDP	-0.12***	-0.14***	-0.10***	-0.25***	-0.06	-0.17***	-0.09**	-0.14***	-0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.00)	(0.03)	(0.00)	(0.00)
General Expectations	-0.07*	-0.07***	-0.06***	-0.12***	-0.08*	-0.06***	-0.08***	-0.07***	-0.03
	(0.08)	(0.00)	(0.01)	(0.00)	(0.06)	(0.00)	(0.01)	(0.00)	(0.40)
Real FX Rate	-2.31	-	-	-	-	-	-	-	-
	(0.14)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
QE1	-0.40	-0.63	-0.58	-	-0.95	-0.76	-0.93	-0.87	0.06
	(0.46)	(0.23)	(0.30)	(-)	(0.17)	(0.39)	(0.21)	(0.44)	(0.96)
QE2	-0.56**	-0.51*	-0.30	-	-0.83	-0.40	-0.18	-0.34	-1.13*
	(0.05)	(0.06)	(0.30)	(-)	(0.29)	(0.19)	(0.72)	(0.38)	(0.10)
QE3	0.17	0.36*	-0.12	0.70**	-0.58	0.53**	0.34	0.18	0.61
	(0.46)	(0.07)	(0.69)	(0.03)	(0.26)	(0.02)	(0.43)	(0.50)	(0.14)
Operation Twist	-0.71***	-0.83***	-0.69***	-0.78**	-1.29**	-0.75***	-0.34	-1.02***	-0.96**
	(0.00)	(0.00)	(0.01)	(0.04)	(0.05)	(0.00)	(0.46)	(0.00)	(0.03)
Age of Customer	0.12***	0.12***	0.11	0.13**	-0.04	0.15***	-0.01	0.19***	0.13
	(0.01)	(0.01)	(0.14)	(0.02)	(0.66)	(0.00)	(0.88)	(0.01)	(0.20)
Age of Customer - Squared	-0.00***	-0.00***	-0.00	-0.00***	0.00	-0.00***	0.00	-0.00***	-0.00
	(0.01)	(0.01)	(0.13)	(0.01)	(0.70)	(0.00)	(0.95)	(0.00)	(0.18)
Education2	0.10	0.10	-0.09	0.26	-0.40	0.18	-0.02	0.15	-0.02
	(0.54)	(0.54)	(0.69)	(0.26)	(0.31)	(0.29)	(0.93)	(0.53)	(0.96)
Education3	-0.83***	-0.83***	-1.02***	-0.63**	-1.37***	-0.72***	-0.88**	-0.92***	-1.16***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)
Education4	-1.27**	-1.27**	-1.08*	-1.32	-0.90	-1.27**	-	-1.49	-1.28*
	(0.02)	(0.02)	(0.09)	(0.20)	(0.41)	(0.04)	(-)	(0.15)	(0.07)
Married	-0.89***	-0.89***	-0.79***	-0.96***	-0.80**	-0.92***	-1.05***	-0.89***	-0.68***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.01)
Term Medium	-0.32**	-0.31**	0.14	-0.39**	0.62	-0.40***	-0.19	-0.37*	0.02
	(0.03)	(0.03)	(0.52)	(0.04)	(0.12)	(0.01)	(0.53)	(0.07)	(0.94)
Term Long	1.17***	1.18***	1.69***	1.20***	-	1.21***	2.06***	1.32***	0.25
	(0.00)	(0.00)	(0.00)	(0.00)	(-)	(0.00)	(0.00)	(0.00)	(0.76)
# of Observations	3980306	3980306	1743875	2236431	1223409	2756897	1440007	1914548	625751

*Note: *** (significant at 1% level); ** (significant at 5% level); * (significant at 10% level). The numbers into parenthesis show the P-values.*

The FX rate has a negative effect on prepayments suggesting that people are less likely to prepay as dollar goes up. The age of the borrower is not statistically significant. Age-squared is significant but with an extremely low magnitude. Education only has a significant effect for individuals with a high school degree and below, implying they are more likely to prepay than university graduates and people with little or no education. Married borrowers are less likely to prepay. The likelihood of prepayment increases as the term lengthens.

Prepayment probability also depends on the prepayment gain ratio which captures the relative gain in prepayment. Replacing the short, medium and long-term dummies with non-linear term variables do not change the results. The length of term has a negative significant effect whereas non-linear terms have near-zero magnitudes albeit being significant. The second version of this regression replaces the prepayment gain ratio with the interest rate of the contract and real mortgage interest rate. Expectations of the future loses significance, signaling that expectations are already embedded in the real mortgage interest rate on the market. QE1 and QE3 suffers magnitude loss. Operational twist, real FX rate and term lengths change signs. Excluding the real FX rate does not change the results as it did in the default case.

Table: 4
Rare Events Logistic Regressions for the Case of Prepayment

	Initial Analyis			**Crisis Effect**		**Initial LTV Ratio**		**Credit Amount**		
	FX Controlled	FX Eleminated	GR Eleminated	During Crisis	After Crisis	Low LTV Ratio	High LTV Ratio	Small Scale	Medium Scale	Large Scale
Constant	-19.15***	-19.51***	-19.07***	-10.65***	-23.57***	-18.60***	-19.89***	-19.46***	-19.47***	-18.42***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
Prepayment Gain Ratio	0.04***	0.05***	-	0.05***	0.06***	0.04***	0.05***	0.05***	0.05***	0.04***
	(0.00)	(0.00)	(-)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Term	5.05***	4.85***	5.94***	5.98***	4.32***	5.42***	4.56***	4.90***	4.93***	5.31***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Term - Squared	-4.22***	-4.09***	-5.11***	-4.32***	-4.16***	-4.47***	-3.83***	-3.70***	-4.28***	-5.54***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Normalized Real GDP	0.05***	0.04***	0.04***	-0.02***	-0.02	0.03***	0.04***	0.04***	0.03***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Real HP over GDP	0.09***	0.09***	0.12***	0.06***	0.21***	0.09***	0.09***	0.10***	0.09***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
General Expectations	0,04***	0,05***	0,00	0,04***	0,06***	0,05***	0,04***	0,05***	0,04***	0,05***
	(0.00)	(0.00)	(0.59)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Real FX Rate	-1.68***	-	2.48***	-	-	-	-	-	-	-
	(0.00)	(-)	(0.00)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
Contract Rate	-	-	120.43***	-	-	-	-	-	-	-
	(-)	(-)	(0.00)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
Real Mortgage Rate	-	-	-500.26***	-	-	-	-	-	-	-
	(-)	(-)	(0.00)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
QE1	0.91***	0.69***	0.12*	0.23***	-	0.54***	0.76***	0.73***	0.53***	0.86***
	(0.00)	(0.00)	(0.07)	(0.00)	(-)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
QE2	0.00***	0.04	0.04	0.32***	-1.91***	0.07	0.03	0.17***	-0.04	0.00
	(0.98)	(0.24)	(0.30)	(0.00)	(0.00)	(0.26)	(0.52)	(0.00)	(0.45)	(0.97)
QE3	-0.97***	-0.90***	-1.36***	-0.77***	-1.00***	-0.91***	-0.89***	-1.01***	-0.88***	-0.75***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Operation Twist	-0.56***	-0.63***	0.14***	-0.50***	-0.44***	-0.71***	-0.58***	-0.58***	-0.60***	-0.76***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Customer	0.01	0.00***	0.00	0.00	0.02***	-0.02**	0.01	-0.02***	0.02**	0.01
	(0.40)	(0.41)	(0.51)	(0.78)	(0.01)	(0.03)	(0.16)	(0.01)	(0.02)	(0.47)
Age of Customer - Squared	-0.00*	-0.00	-0.00*	-0.00	-0.00***	0.00	-0.00	0.00*	-0.00***	-0.00
	(0.10)	(0.11)	(0.09)	(0.61)	(0.00)	(0.38)	(0.22)	(0.08)	(0.01)	(0.28)
Education2	0.09***	0.09***	0.09***	0.02	0.17***	0.03	0.11	0.02	0.15***	0.00
	(0.00)	(0.00)	(0.00)	(0.63)	(0.00)	(0.44)	(0.44)	(0.56)	(0.00)	(0.97)
Education3	0.10***	0.10***	0.13***	0.01	0.24***	-0.03	0.16	0.05	0.11***	-0.06
	(0.00)	(0.00)	(0.00)	(0.81)	(0.00)	(0.55)	(0.55)	(0.21)	(0.01)	(0.43)
Education4	0.06	0.06	0.11**	-0.06	0.23***	-0.12	0.16***	-0.08	0.10	-0.12
	(0.21)	(0.22)	(0.02)	(0.35)	(0.00)	(0.11)	(0.01)	(0.45)	(0.16)	(0.22)
Married	-0.16***	-0.16***	-0.14***	-0.11***	-0.18***	-0.14***	-0.17***	-0.12***	-0.20***	-0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term Medium	0.14***	0.15***	-0.32***	0.36***	0.14***	0.23***	0.08***	0.18***	0.12***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term Long	0.53***	0.56***	-0.46***	0.94***	0.52***	0.83***	0.48***	0.60***	0.69***	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.95)
# of Observations	3980306	3980306	3980306	1743875	2236431	1223409	2756897	1440007	1914548	625751

*Note: *** (significant at 1% level); ** (significant at 5% level); * (significant at 10% level). The numbers into parenthesis show the P-values.*

Dividing the sample in two for the crisis and post crisis periods suggest that the second quantitative easing had a positive effect during the crisis and a negative one afterwards. The size of the GDP has no effect in the post-crisis period. Demographic variables of age and education were not significant during the crisis, but they became so in the post-crisis months.

Separating the low and high initial LTV borrowers suggest that education only has an effect when the credit has high initial LTV. Curiously, this only pertains to the ratio of the LTV and not to the amount of actual credit.

Table: 5
First Difference and Relative Risk of Probabilities for Deafult and Prepayment

	Default First Difference (Change in Probability, %)	**Default** Relative Risk (Return in Probability, %)		**Prepayment** First Difference (Change in Probability, %)	**Prepayment** Relative Risk (Return in Probability, %)
LTV	0.001	1.195	Prepayment Gain Ratio	0.015	1.053
Age of Term	0.001	1.191	Age of Term	0.031	1.110
Age of Term - Squared	-0.000	0.947	Age of Term - Squared	-0.009	0.967
Normalized Real GDP	-0.001	0.755	Normalized Real GDP	0.207	1.719
Real HP over GDP	-0.003	0.452	Real HP over GDP	0.246	1.863
General Expectations	-0.003	0.519	General Expectations	0.137	1.484
Real FX Rate	-0.001	0.754	Real FX Rate	-0.052	0.817
QE1	-0.002	0.644	QE1	0.412	2.476
QE2	-0.002	0.570	QE2	-0.000	1.001
QE3	0.001	1.194	QE3	-0.281	0.378
Operation Twist	-0.003	0.497	Operation Twist	-0.138	0.571
Age of Customer	0.003	1.608	Age of Customer	0.006	1.020
Age of Customer - Squared	-0.001	0.784	Age of Customer - Squared	-0.005	0.981
Education2	0.001	1.115	Education2	0.024	1.086
Education3	-0.004	0.439	Education3	0.029	1.102
Education4	-0.004	0.278	Education4	0.017	1.061
Married	-0.007	0.411	Married	-0.048	0.852
Term Medium	-0.002	0.731	Term Medium	0.039	1.151
Term Long	0.013	3.163	Term Long	0.197	1.710

Note: First Difference indicates the amount of increase or decrease, while Relative Risk gives the percentage change in the probability of each early termination case with respect to 10% increase from mean values for given variable. For dummy variables, the values in the table are calculated by changing the to 1 from 0. All the values at the table are reached via "relogitq" command in Stata.

Dividing the sample based on credit scale shows that education only has an effect when the credit is medium-scale except for higher education. The observed effect of education on the medium scale credits is positive. Age only has a negative effect on prepayment for small-scale credits and a positive one in medium scale credits. The long-term credit dummy loses its significance in the large-scale credit case.

6. Concluding Remarks

Our study aims to highlight the patterns and relationship observed between defaults and prepayments and other relevant variables in the Turkish mortgage market through an analysis of commercial data. The methods we develop aims to use available static data by converting it into a panel format since most of the credits have not reached their maturity.

By doing so, we can determine not only if a borrower will default but also predict when it is most likely to happen. We also include dummy variables for FED policies to show how an emerging market would depend on international conditions. Our dynamic regressions suggest that default is positively affected by a high loan to value ratio, age of the borrower, length of term and negatively affected by certain quantitative easing periods, operational twist, and a high school and above education level, good expectations regarding the future and the ratio of real house prices to the size of the economy. The likelihood of default is locally maximized when 62% of the term is reached. Prepayment is positively affected by the prepayment gain ratio, the first quantitative easing, an education level of high school and above, the size of the GDP, the ratio of real house prices to GDP and negatively affected by the third quantitative easing period, operational twist, real FX rate and marriage. Probability of prepayment is maximized around 60% of the term. The significance and magnitude of coefficients in both default and prepayment regressions slightly change when the sample is divided based on credit scale, initial LTV and crisis periods.

Our findings about the Turkish mortgage market are crucial in the sense that it gives valuable signals to mortgage creditors about the timing of default risk and prepayment behaviours. Also, this study creates useful ground for a better understanding of the default and prepayment attitudes by examining the impacts of macroeconomic and demographic variables. Hopefully, we aim to enlarge this study by focusing on different dataset and various emerging economies.

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