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Loan-to-Value Policy as a Macroprudential Tool: The Case of Residential Mortgage Loans in Asia

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Abstract

Credit creation in the housing market has been a key source of systemic financial risk, and therefore is at the center of the debate on macroprudential policies. The loan-to-value (LTV) ratio is a widely used macroprudential tool aimed at moderating mortgage loan creation, and its effectiveness needs to be estimated empirically. This paper is unique in that it analyzes the effect of LTV on mortgage lending, the direct channel of influence, using a large sample of banks in 10 Asian economies. It uses estimation techniques to deal with the large presence of outliers in the data. Robust-to-outlier estimations show that economies with LTV polices have expanded residential mortgage loans by 6.7% per year, while non-LTV economies have expanded by 14.6%, which suggests LTV policies have been effective.

JEL Classification: C23, E58, G21, G28

Contents

1. INTRODUCTION

The global financial crisis (GFC) of 2007–2009 underlined the need for central banks and financial regulators to take a macroprudential perspective on financial risk, i.e., to monitor and regulate the buildup of systemic financial risk in the economy as a whole, as opposed to simply monitoring the condition of individual financial institutions (microprudential regulation). This has been highlighted in numerous reports, e.g., G30 (2009); IMF (2009), Brunnermeier et al. (2009); and TdLG (2009). The regulatory response to this in the advanced economies, under the guidance of the G20 and the Financial Stability Board, has tended to focus on strengthening the liability side of banks' balance sheets by enforcing stricter capital adequacy requirements, including the introduction of a countercyclical buffer, and the introduction of liquidity requirements (see, e.g., BIS 2010a).

However, financial crises can also be mitigated by improving the asset side of banks' balance sheets, i.e., reducing the risk that they will make poor loans that ultimately become non-performing loans (NPLs), and increasing the amount that can be recovered from NPLs. Such measures broadly restrain banks from lending excessively during boom periods, and also tend to reduce the losses they may incur during downturns. Central banks or financial regulators (depending on which entity has responsibility for supervising banks) can use a number of macroprudential tools to restrain the buildup of NPLs, including loan-to-value (LTV) ratios, debt-service-to-income ratios, credit exposure limits on specific sectors (especially real estate), underwriting standards, and limits on loan growth, among others. Sometimes these tools are fixed, while in other cases they can be altered in a discretionary way according to the authorities' assessment of the economic and financial situation. Many macroprudential tools were originally developed for use as microprudential tools (LTV ratios and exposure limits, among others) at the individual bank level, but can be adapted to macroprudential use by calibrating them in relation to the macro-financial cycle. Although these kinds of measures generally lost favor in advanced economies, they have been actively used in Asian economies. Table 1 provides a summary of macroprudential measures used in Asia.

LTV ratios cap the percentage of the value of an asset that can be financed by a bank loan, thereby ensuring an adequate cushion of collateral value for the loan in case it should sour. A good description of issues related to them can be found in Borio, Furfine, and Lowe (2001). Table 1 shows that LTV ratios are the most commonly used macroprudential policy measure in the region. Some economies impose LTV ratios all the time, while others impose them only as needed. Table 2 shows the normal levels of LTVs for property lending used in a number of economies, typically either 70% or 80%. Debt-service-to-income (DTI) ratios are an alternative to LTV ratios, and enforce minimum levels of the expected ability of borrowers to service debt, providing another cap on excessive lending. Their use in Asia is more limited than that of LTV ratios, as they have been implemented only in the People's Republic of China (PRC); Hong Kong, China; and the Republic of Korea. This probably partly reflects difficulties in obtaining and verifying income data in other economies. Typically, they have been implemented together with LTV ratios.

Table 1: Asian Experience with Macroprudential Policy Tools

Objective	Tools	Examples
Manage aggregate risk over time (procyclicality)	Countercyclical provisioning	PRC; India
	Loan-to-value ratios	PRC; Hong Kong, China; Indonesia; Japan; Republic of Korea; Malaysia; Philippines; Singapore; Thailand
	Debt-service-to-income ratios	PRC; Hong Kong, China; Republic of Korea
	Tighter lending criteria	PRC; Hong Kong, China; Republic of Korea; Malaysia; Philippines; Singapore; Thailand
	Credit limits	PRC; Hong Kong, China; India
	Tighter supervision	PRC; Hong Kong, China; India; Republic of Korea; Malaysia; Singapore
	Capital requirements	India; Malaysia
	Exposure limits on lending to specific sectors	Republic of Korea; Malaysia; Philippines; Singapore
Manage aggregate risk at every point in time (systemic oversight)	Capital surcharges for systemically important banks	PRC; India; Philippines; Singapore
	Liquidity and funding requirements	PRC; India; Republic of Korea; Malaysia; Philippines; Singapore; Thailand
	Loan-to-deposit requirements	PRC; Republic of Korea
	FX exposure limits	Republic of Korea; Philippines
	Limits on currency mismatches	India; Malaysia; Philippines

PRC = People's Republic of China.

Sources: BIS (2010b); Lamberte, Manlagñit, and Prativedwannakij (2010); Sheng (2010).

Table 2: Caps on Loan-to-Value (LTV) Ratios for Property Lending in Asia

Economy	Max. LTV Ratio New Loans (%)	Typical Loan Term (Years)	Mortgage Rate
Hong Kong, China	70	20	ARM
Indonesia	80	15 (max. 20)	ARM
Japan	80	20–30	ARM
Korea, Rep. of	70	3–20	ARM
Malaysia	80	30	ARM
Philippines	70	10–20	ARM
PRC	80	10–15 (max. 30)	ARM
Singapore	80	30–35	ARM
Thailand	80	10–20 (max. 30)	ARM

ARM = Adjustable Rate Mortgage; PRC = People's Republic of China.

Source: Lamberte, Manlagnit, and Prativedwannakij (2010).

In this paper, we analyze the effectiveness of LTV as a macroprudential tool on the growth of residential mortgage loans (RML) in 10 Asian economies. The key empirical question is the extent to which LTV can inhibit the growth of bank lending. Our benchmark hypothesis is that the cap of LTV would restrain the growth of RMLs relative to the case of no LTV cap. The overall growth of mortgage loans of banks in these Asian economies in this period has generally been quite high. Even after disregarding extreme values, the robust mean growth rate is 7.8%. The high growth rate of mortgage lending in these economies may explain why the use of LTV has been so active in the region. Robust estimates suggest the growth rates of mortgage loans in LTV and non-LTV economies are 14.8% and 6.7%, respectively. Of this 8.1 percentage-point difference, we find that LTV explains 5.6 percentage points directly, and even more once its indirect effects on other predictors are considered.

This paper adds to the growing literature on the effectiveness of LTV as a macroprudential policy tool. Most studies have focused on the impacts of LTV policies on macro-level variables such as total bank credit or housing prices. Ours is one of the few studies that analyze bank-level responses to LTV policies, and the first one to look directly at the mortgage market. Since LTV policies target mortgage loans, this is the item in banks' balance sheets that should be analyzed rather than some measure of overall financial stability, as in much of the previous literature. Other studies with a bank-level approach include Claessens et al. (2013) and Wang and Sun (2013). This study makes a number of contributions to the literature in this area. First, it comprehensively deals with problems of outliers in a large and diverse panel data set of banks using robust-to-outlier methods. Empirical studies based on a least-squares approach would be highly sensitive to the large number of outliers detected. Second, it uses a number of different techniques to isolate the differences in behavior of mortgage markets between economies that use or do not use LTVs. We go beyond the linear specification, in similar spirit to Wong et al. (2011). The findings generally support those of other studies that LTV ratios can reduce the overall growth rate of housing loans and thereby contribute to financial and economic stability.

The rest of the paper is organized as follows. The next section presents an overview of previous studies of LTV and other macroprudential policies on measures of credit growth, housing prices, and financial stability. Section 3 describes the data sources and methodologies used, the latter including robust regression, the introduction of some non-linearities, and the application of the Blinder-Oaxaca decomposition. The results of our empirical analysis can be found in Section 4. Section 5 provides some conclusions.

2. EFFECTIVENESS OF LOAN-TO-VALUE AS A MACROPRUDENTIAL TOOL: EXISTING LITERATURE

The practice of macroprudential regulation in containing systemic risk has been very important, especially after the global financial crisis (GFC). Although Asia was not primarily affected by the financial channel during the GFC, financial regulators in Asia are also paying much attention to the effective use of possible macroprudential tools, predominantly the LTV ratio. Indeed, some of these tools were used effectively after the experience of the Asian financial crisis of 1997. The case of Hong Kong, China, with more than 20 years of LTV policy, has been pioneering in the region, and has been used extensively as a study case in the topic. In this section, we review the literature on the effectiveness of LTV as macroprudential policy tool. Most of these studies found evidence in support of the use of LTV policy.

Claessens et al. (2013) concluded that the use of macroprudential policy tools can be important to mitigate overall systemic risk, especially for countries that are exposed to international shocks. The effectiveness of LTV was investigated by including dummy variables for the years when the policy was actually implemented on three variables: leverage growth, asset growth, and growth in the ratio of noncore to core liabilities. Their sample of about 2,800 banks in 48 countries was taken from Bankscope[1] and included both advanced and emerging economies. The authors found that LTV is an effective policy tool in reducing all three variables during boom periods. Furthermore, they found that other policies like caps on debt-to-income ratios and limits on credit growth and foreign currency lending are also effective in reducing the bank risk variables. In another cross country study, Lim et al. (2011) looked into the effectiveness of LTV along with seven other policy tools in reducing four measures of systemic risk: credit growth, liquidity, leverage, and capital flows. They found that many of the frequently used policy instruments, including LTV, are effective in reducing pro-

[1] http://www.bvdinfo.com/en-gb/.

cyclicality, and their effectiveness is sensitive to the type of shock facing the financial sector. In a similar study, Crowe et al. (2011) found that an aggressive use of LTV in a countercyclical manner would help to stabilize the business cycle, both during market upturns and downturns.

Some studies carried out on Asian experiences of LTV policy also found positive results. Wong et al. (2011) examined the impact of LTV on mortgage delinquency ratios and various measures of property market activity, including property prices and household leverage. In a panel study of 13 economies, they found that the presence of LTV significantly reduced mortgage delinquency ratios. In a separate analysis of Hong Kong, China; the Republic of Korea; and Singapore, they found that tightening LTV caps tended to result in lower household mortgage debt leverage in Hong Kong, China; and Singapore, although the impact on property prices and transaction volumes was not significant. The Korean experience of macroprudential policy was analyzed by Igan and Kang (2011). They examined the impact of LTV and DTI limits on house price dynamics, residential real estate market activity, and household leverage. Their findings suggest that prudent LTV policy could curb expectations and speculation, thereby helping to limit mortgage credit growth. Several studies carried out on the experience of Hong Kong, China also suggest that LTV has been effective in increasing the resilience of the banking sector.[2] The Chinese experience in the use of LTV is not as clear as that of Hong Kong, China as reported by Wang and Sun (2013). They suggested that, compared to LTV, the required reserve ratio (RRR) seemed to be a more successful policy variable in containing systemic risk in the PRC.

Some studies raised doubts about the effectiveness of LTV. Primarily focusing on the Irish experience, Duffy (2012) argued that the effectiveness of LTV as policy tool is not conclusive, especially given the fact that this policy is used in conjunction with other monetary and fiscal policies. In another study covering central, eastern, and southeastern European countries that analyzed various macroprudential policy tools, Vandenbussche, Vogel, and Detragiache (2012) found that LTV does not have a significant impact on housing prices although it had the expected sign.

Most of the literature is general in nature because it analyzes the use of LTV together with other policy tools on a set of financial stability variables. In contrast, this, as far as we are aware, is the only paper that specifically analyzes the effect of LTV on the growth of residential mortgage loans by individual banks. We believe this is important, since LTV operates directly on residential mortgage loans by banks.

3. EMPIRICAL STRATEGY

Our empirical strategy relies on bank-specific information, which varies widely across banks, as well as country-level data, resulting in a quite heterogeneous sample with a large proportion of outliers. Therefore, an alternative method to the classical ordinary least squares (OLS) is considered—the MM-estimator, which uses “weights” to handle extreme values. The weights of observations identified as outliers are reduced to minimize their influence. The MM-estimator is resistant to different types of outliers (vertical outliers, bad leverage points, and good leverage points) and is suitable for panel data. In comparison, quantile regression, another commonly used robust estimator, does relatively well dealing with vertical outliers but does not cope appropriately with bad leverage points, while other robust estimators, such as the M-estimator, may not cope with the existence of clusters of outliers.

[2] For example, see Wong et al. (2004); Gerlach and Peng (2005); and Craig and Hua (2011).

In addition, to check the robustness of our results, an alternative functional form is considered with LTV interaction terms where LTV affects not only mortgage loans but also the impacts of the other determinants of the dependent variable. Furthermore, the analysis is extended using the Blinder-Oaxaca counterfactual decomposition procedure, a more comprehensive methodology where observations are divided in two groups—cases with and without LTV policies. Also, the decomposition takes into account the large number of outliers making use of the MM-estimator and robust means. The difference in (robust) means of mortgage loan growth is computed and explained by three components: endowments, coefficients, and interactions effects.

3.1 Model Specification

To assess the effectiveness of the LTV policy as macroprudential tool on the mortgage loan market, our empirical strategy compares economies and years where the policy was implemented with alternative country-year combinations where the policy was not used. Residential mortgage loans (RML) of bank *i* can be described as a function of both individual bank conditions and macroeconomic country *j*-specific variables, included in the vectors Z and X, respectively:

$$RML_{it} = \beta_0 + \Gamma X_{jt} + \Psi Z_{it} + \lambda_t + u_{it} \quad (1)$$

where t is time, u_{it} is the error term, and λ_t are time effects. Bank or country fixed effects could be introduced in either Z or X, respectively. In this framework, if LTV policies were effective in controlling mortgage loans, expansion equation (1) could be modified to include this variable:

$$RML_{it} = \beta_0 + \beta_1 LTV_{jt} + \Gamma X_{jt} + \Psi Z_{it} + \lambda_t + u_{it} \quad (2)$$

After controlling for bank- and country-specific conditions, the objective is to look at the sign and magnitude of the parameter on LTV (β_1). A significantly negative coefficient of LTV would imply that macroprudential policy has achieved the expected outcome of reduced mortgage loan creation.

3.2 Data and Outliers

This study uses annual unbalanced panel data of 201 banks, with time periods ranging from two to seven years. Around 75% of the banks have five observations at most. These samples of banks were taken from 10 Asian economies: the PRC; Hong Kong, China; India; Indonesia; the Republic of Korea; Malaysia; Philippines; Singapore; Taipei,China; and Thailand. Depending on the equation specifications, the total number of observations ranged from 500 to over 700.

Table 3: Data Sources

Variable	Source	Expected Sign
Dependent variable		
Residential mortgage loans	Bankscope	
Main variable of interest		
Loan-to-value ratio policy	Borio and Shim (2007) and central banks	–
Bank-specific variables		
Customers' Deposits	Bankscope	+
Non-performing loans	Bankscope	+/–
Interest to Non-Interest Income ratio	Bankscope	+
Liquid Assets	Bankscope	–
Economy-specific variables		
Nominal interest rate	IMF, DGBAS (for Taipei,China)	–
Real interest rate	IMF, DGBAS (for Taipei,China)	–
Nominal stock price index	Yahoo Finance	–
Current account balance	IMF, DGBAS (for Taipei,China)	+
Real exchange rate	IMF	+
Real GDP index	World Bank, DGBAS (for Taipei,China)	+
Real house price index	GPG, National Housing Bank (India), Bank Indonesia, Bank of Thailand	–
CPI inflation	ADB	–
CPI inflation forecast	ADB	–
Real GDP index forecast	ADB (ADO), IMF (WEO)	+
Mortgage insurance policy	Individual central banks	+

Notes: ADB = Asian Development Bank; ADO = Asian Development Outlook; CPI = consumer price index; DGBAS = Directorate General of Budget, Accounting and Statistics; GPG = Global Property Guide (available at www.globalpropertyguide.com); IMF = International Monetary Fund; WEO = World Economic Outlook.

Sources: Asian Development Bank Statistical Database System (SDBS) database (http://www.adb.org/data/sdbs), accessed 17 March 2014; Bank Indonesia Indonesian Financial Statistics database (http://www.bi.go.id/en/statistik/seki/bulanan/Pages/SEKI-May2014.aspx), accessed 5 March 2014; Bank of Thailand statistical database (https://www.bot.or.th/English/Statistics/Pages/default.aspx), accessed 7 September 2014; Bureau van Dijk Bankscope database (https://bankscope.bvdinfo.com/version-201556/home.serv?product=scope2006), accessed 15 March 2014; Global Property Guide (GPG) (http://www.globalpropertyguide.com), accessed 13 March 2014; Director General of Budget, Accounting and Statistics (DGBAS), Executive Yuan, Taipei,China (http://eng.dgbas.gov.tw/mp.asp?mp=2), accessed 12 March 2015; International Monetary Fund statistical database (http://www.imf.org/external/data.htm), accessed 11 March 2014; National Housing Bank (India) database (http://www.housingindia.info/NHBStatistics.aspx), accessed 28 February 2014; World Bank World Databank (http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=jobs), accessed 26 February 2014; Yahoo Finance (http://finance.yahoo.com/market-overview/), accessed 23 February 2014.

Table 4: Summary Statistics Table

Variable	Obs.	Robust Mean	Mean	Std. Dev.	Skewness	Kurtosis
Residential mortgage loans (logs)	788	9.5628	9.1482	2.4520	–0.5799	3.2992
Customers Deposits (logs)	780	11.60	11.64	1.84	–0.07	4.25
Non-perf. Loans, % of gross loans	763	1.2890	2.6604	4.1086	8.9083	144.96
Interest to Non-Interest Income ratio	734	0.1549	0.2230	0.3890	12.7723	264.99
Liquid Assets, % of Tot. Dep. & Bor.	697	21.731	24.384	14.211	1.691	9.417
Nominal interest rate	788	5.8232	6.2906	2.5134	1.2376	5.1152
Real interest rate	788	3.3922	3.9440	2.7124	0.5817	3.5241
Nominal interest rate differential	788	1.2691	1.6597	2.5875	0.9038	4.4794
Real interest rate differential	788	–1.0926	–0.6870	2.9821	0.3329	2.9000
Nominal Stock Price Index (logs)	788	0.3220	0.4178	0.3946	0.4079	2.1657
Current account, % of GDP	788	5.2149	6.8689	6.5010	1.1065	4.1837
Real Exchange Rate (logs)	788	4.5360	4.5101	0.0999	–0.6662	2.8132
Real Exchange Rate, St. Dev. (logs)	788	0.0167	0.0208	0.0179	1.7833	7.3303
Real GDP index, 2005=100, (logs)	788	4.7957	4.8540	0.1813	0.5604	2.5093
Real House Price Index, 2005=100, (logs)	761	0.2196	0.1744	0.2279	–0.6911	2.8677
CPI inflation	788	2.2672	2.3467	3.2339	0.4659	5.6089
CPI inflation, St. Dev.	788	0.1705	0.2229	0.6059	0.1877	3.5754
CPI inflation forecast	786	2.7159	2.9217	1.6685	0.9585	6.8998
Real GDP index forecast (logs)	786	4.8169	4.8833	0.1981	0.5951	2.3374

Variable	Obs.	Robust Mean	Mean	Std. Dev.	Skewness	Kurtosis
Residential mortgage loans (logs-FD)	573	0.0777	0.1615	0.4627	6.0159	70.800
Customers Deposits (logs- FD)	567	0.1152	0.1486	0.2230	1.7334	11.596
Non-perf. Loans, % of gross loans (FD)	554	–0.2586	–0.4843	1.7151	–2.5949	41.693
Interest to Non-Interest Income ratio (FD)	534	0.0002	–0.0153	0.2920	–0.8518	65.435
Liquid Assets, % of Tot. Dep. & Bor. (FD)	502	0.3319	0.3442	6.9493	0.1314	7.8338
Nominal interest rate (FD)	573	0.1421	–0.1165	1.0798	–0.5962	4.5211
Real interest rate (FD)	573	–0.4235	–0.0657	3.2790	0.2290	2.6697
Nominal interest rate differential (FD)	573	0.5610	0.5528	1.2626	–0.4136	4.2343
Real interest rate differential (FD)	573	–0.4403	0.6036	3.6314	0.8405	3.1312
Nominal Stock Price Index (logs-FD)	573	–0.0177	0.0128	0.2076	1.0851	6.2608
Current account, % of GDP (FD)	573	–5.6877	–0.7677	10.5390	0.7057	2.4290
Real Exchange Rate (logs-FD)	573	–0.0124	–0.0206	0.0585	–0.0930	4.4823
Real Exchange Rate, St. Dev. (logs-FD)	573	0.0003	–0.0001	0.0178	–0.0545	7.6941
Real GDP index, 2005=100, (logs-FD)	573	0.0750	0.0604	0.0394	–0.7227	2.6832
Real House Price Index, 2005=100, (logs-FD)	546	0.0378	0.0353	0.1013	–0.3726	3.6132
CPI inflation (FD)	573	0.4671	–0.0508	3.4547	–0.6232	3.3704
CPI inflation, St. Dev. (FD)	573	–0.0716	–0.0191	0.5242	0.1997	3.6466
CPI inflation forecast (FD)	571	0.2510	0.0688	2.1164	–0.5997	3.6619
Real GDP index forecast (logs-FD)	571	0.0708	0.0593	0.0617	–0.4380	3.4375

CPI = consumer price index; FD = first difference; GDP = gross domestic product; logs = logarithmic transformation; Non-perf. Loans = Non-performing Loans; Obs. = observations; Std. Dev. = standard deviation; Tot. Dep. & Bor. = total deposits and borrowing.

Note: For a convenient benchmark, the normal distribution is characterized by a skewness of zero (symmetry) and kurtosis of three (not very fat tails).

Source: See Table 3.

The bank-specific Z variables and economy-specific X variables were chosen based on previous studies of determinants of bank loans and bank profitability. The details on variables, their sources, and expected signs are provided in Table 3. All the bank-specific variables were collected from the Bankscope database, including the dependent variable, RML. The macroeconomic variables came mostly from the International Monetary Fund (IMF), Asian Development Bank (ADB), and World Bank database, complimented with other country sources. Our main variable of interest—dummy of LTV policy if it is being used in any particular year in a particular economy—

was initially obtained from Borio and Shim (2007). However, given that the information needed to be updated for the later years, we supplemented this with information published by individual central banks. Further information was collected from other media reports and documents.

One of the major issues to handle is the existence of outliers. This was especially true for the bank-specific variables and in particular the dependent variable, RML. The summary statistics of the variables in the model show a high degree of skewness and kurtosis (Table 4). Furthermore, the gap between the minimum and maximum values of some of the variables is very high (for example, 1.4 vs 14.5 for RML, 1.68 vs 16.7 for deposits, 0.00 vs 77 for NPLs, and 1.080 vs 124.8 for liquid assets). Under such circumstances, the traditional OLS could be biased and inefficient. Instead, we turn our attention to robust-to-outlier estimators.

3.3 Robust Regression Estimators

The basic idea of robust regression is that the sample data is most likely a mixture of two components: the "true model" whose coefficients we want to estimate using a regression line, and some other process (or more than one) that contaminates the data. If these contaminated data points are far away from the central tendency of the variables, they will deviate substantially from the true regression line. It is well known that the method of least squares is very sensitive to these outliers. Even a small proportion of outliers in a sample may bias the estimates considerably. Robust regression estimators are able to deal with a high degree of contamination of outliers.

The two key properties of a robust estimator are efficiency and the breakdown point. The trade-off between unbiasedness and efficiency in the presence of outliers is central to the relative strengths of robust regression and least squares. We define relative efficiency of an estimator relative to OLS[3] as the ratio of the standard errors of OLS and the estimator of interest. An efficiency of 100% would imply the standard error of the robust estimator is as small as the OLS standard error. The breakdown point is the percentage of outliers in the sample the estimator would tolerate before the bias became large. A breakdown of 50% (the maximum possible) means the robust estimator resists contamination of outliers in the sample of up to 50%. For example, the least squares regression has an efficiency under normality of 100% and a breakpoint of 0% while the mean regression has an efficiency under normality of 64% and a breakpoint of 50%.

Huber (1964), followed by others, expanded robust regression to the M-estimators, which are aimed to improve the efficiency of robust regression while still dealing with outliers. This estimator relies on weights that may reduce the influence of outliers in the coefficients. A weight of zero would be equivalent to eliminating completely the observation from the analysis. In practice, robust regression is based on some sort of weighted least squares according to an iterative algorithm where the weights are computed at each iteration. True parameters may be recovered even if there are many outliers. An example of an M-estimator with high efficiency is that of Li (1985). However, this first generation of robust estimators has a low breakpoint. A second generation of estimators was developed to obtain a high breakpoint, such as the S-

[3] Behind this are the Gauss–Markov theorem and the best linear unbiased estimator (BLUE) property of OLS. Further, OLS is the most efficient of all linear and nonlinear estimators under the assumption of normality. However, departures from homoskedasticity and normality may affect the efficiency of least squares considerably.

estimator of Rousseeuw and Yohai (1987) and others[4]. These estimators usually have a resistance of 50% but they may have low efficiency (often less than 30%), so the estimates may be unbiased but have an increased variance compared to estimates from least squares. Therefore, the larger the presence of outliers, the better the performance of the S-estimator. Finally, the MM-estimator emerged, which combines the high breakpoint of the S-estimators (50%) and the high efficiency of the M-estimators. It is based on the iterative weighted least square algorithm of the M-estimator where the starting value is given by the S-estimator. This estimator was first introduced by Yohai (1987) and its efficiency properties in small samples have been studied by Maronna and Yohai (2010) and Koller and Stahel (2011).

The efficiency level may be chosen, taking into account that higher efficiency would be associated with a higher bias: our choice here is an efficiency of 70%, as favored by Verardi and Croux (2009), based on their simulation results. Since year effects are included, making use of year dummies and our main variable of interest is also a dummy variable, the MM-estimator used here is the extended version for fixed effects panel data models suggested by Bramati and Croux (2007).[5] This MM-estimator was developed for panels with relatively small T. For inference, standard errors robust to heteroskedasticity and asymmetric errors are computed based on Croux, Dhaene, and Horelbeke (2003). Therefore, the coefficient estimates are reliable in the presence of outliers, their standard errors take into account the presence of heteroskedasticity, asymmetry, and outliers, the nature of dummy variables is taken into account when necessary, and a good mix of efficiency (70%) and resistance to outliers (50%) is achieved.

Two standard practices in applied work may be compared to the robust MM-estimator. First, the use of some variable transformation to obtain thinner tails relies on the proper identification of the type of outliers in the data. Even if successful, this would be a strategy with high efficiency but low breakpoint: the remaining few outliers may still seriously affect the results. Second, it is common practice to drop observations in some ad hoc fashion to avoid outliers. For example, eliminating some fixed proportion of the most extreme values (1% to 5% of the top and bottom) of each variable,[6] implying a low breakdown level. Likewise, the graphic approach to outlier identification, such as looking at scatterplots to detect rare observations, may have the same low breakdown point limitation since it is a generalization to the two-dimensional plane. In addition, the correct use of a low but positive weight rather than dropping an observation may also imply a gain in efficiency.

More importantly, not only does the robust regression approach provide a higher breakdown point, the weight is a superior measure of outlierness. The weight can be treated as an index of outlierness (the closer to zero, the larger the outlierness), which is computed taking into account all the dimensions of the dataset at the same time. In contrast, detection of extreme observations of one or two variables at a time is not feasible when the dimensionality of the data increases. Relying on other single-variable measures such as the kurtosis would face the same limitation.

[4] Other examples are: median regression, quantile regression, and some of their extensions.

[5] Otherwise, the S-estimator used as initial weights does not perform well in the presence of dummy variables.

[6] Notice it is not clear how many observations should be dropped. Also, dropping a significant number of observations may be reasonable when having thousands of observations, but not when having hundreds.

3.4 Loan-to-Value Effects: Nonlinearities

The simple relationship in (2) may be expanded to consider richer differences between economies with and without LTV. A natural expansion of our analysis would allow for interaction terms of the other variables with LTV, augmenting equation (2) as:

$$RML_{it} = \beta_0 + \beta_1 LTV_{jt} + \Gamma X_{jt} + \Upsilon(LTV_{jt} \times X_{jt}) + \Psi Z_{it} + \Lambda(LTV_{jt} \times Z_{it}) + \lambda_t + u_{it} \quad (3)$$

This is a more general functional form than adding an LTV dummy variable. Presented in this way, the policy question now is not only whether LTV has a significant effect on mortgage loans, but also whether the relationship between mortgage loans and its other determinants is affected by the presence or absence of LTV policy. For example, an important justification for LTV policies is to reduce the responsiveness of mortgage loans to house prices and macroeconomic conditions that otherwise may encourage credit booms. This type of hypothesis can be tested looking at the significance of the coefficients in Υ and Λ.

If so, the parameters in relationship (1) would be different for economies with and without LTV. This is equivalent to having different regression lines of equation (1) for the two groups of observations: when LTV=0 (group 1) and LTV=1 (group 2).[7]

$$RML_{it} = \beta_0^{LTV=0} + \Gamma^{LTV=0} X_{jt} + \Psi^{LTV=0} Z_{it} + \lambda_t^{LTV=0} + u_{it} \quad (4)$$

$$RML_{it} = \beta_0^{LTV=1} + \Gamma^{LTV=1} X_{jt} + \Psi^{LTV=1} Z_{it} + \lambda_t^{LTV=1} + u_{it} \quad (5)$$

and testing whether any coefficients are the same for LTV=0 and LTV=1.

3.5 Blinder-Oaxaca Decomposition

The empirical framework of equations (4) and (5) can be taken further to compare mortgage loan growth of the two groups taking into account group differences in not only the coefficients' estimates, but also in the mortgage loan determinants. For this, we will borrow an often-used methodology to study labor market outcomes by groups, such as wage differentials between male and female workers (i.e., the wage gap)—the Blinder-Oaxaca decomposition (see Weichselbaumer and Winter-Ebmer 2005, for a survey). This decomposition is based on separate individual regressions for the LTV and non-LTV groups of equation (1).[8] Equation (1) can be rearranged into the following matrix form:

$$y = Y'\Omega + u \quad (6)$$

where the mortgage loan variable is stacked in vector y for all i and t; and both economy- and bank-specific variables are grouped in matrix Y. The vector Ω includes the parameters from both Γ and Ψ in (1). The new error term is an augmented version of the error term in (1), which has all banks ordered one below the other. The model is

[7] Also, having separate regressions is more flexible since the variance of the error term is estimated separately. That is, equation (3) imposes the additional constraint that the variance of the error term is the same for both LTV=0 and LTV=1. Additionally, as we will see later, having separate regressions allows us to decompose the total effect three ways.

[8] The LTV variable becomes unnecessary once separate regressions are estimated for each group.

fitted separately for the two groups, LTV equal to zero and one, as in (4) and (5). We begin by expressing the mean difference of y as the difference in the linear prediction of the group-specific means of the regressors in Y:

$$R = E(y^{LTV=1}) - E(y^{LTV=0}) = E(Y^{LTV=1})'\Omega^{LTV=1} - E(Y^{LTV=0})'\Omega^{LTV=0} \tag{7}$$

Following Daymont and Andrisani (1994), this can be expressed as the following threefold decomposition:[9]

$$R = [\,E(Y^{LTV=1}) - E(Y^{LTV=0})]'\Omega^{LTV=0} + E(Y^{LTV=0})'[\Omega^{LTV=1} - \Omega^{LTV=0}] + [\,E(Y^{LTV=1}) - E(Y^{LTV=0})]'[\Omega^{LTV=1} - \Omega^{LTV=0}] \tag{8}$$

The first component accounts for differences in endowments (E) between the two groups, i.e., group difference in the regressors. The second component is the difference in the coefficients (including the intercept). The third component is an interaction term to take into account that differences in endowments and coefficients between the two groups happen simultaneously. The results should be interpreted from the perspective of the $LTV = 0$ group. The endowment effect measures the expected change in the $LTV = 0$ group mean outcome if the $LTV = 0$ group had the level of the regressor variables of the LTV=1 group. Likewise, the coefficient effect is the expected change in the mean outcome if the $LTV = 0$ group had the coefficients of the $LTV = 1$ group. This is a potentially interesting result, because it allows us to make a clear distinction between the case of differences in the mortgage market because of economies having different levels of some of their fundamental variables and the effects of LTV on the relationship between mortgage loans and these determinants.

At the same time, these three aggregate components—-endowments, coefficients, and interactions—can be decomposed into the contributions of individual variables, providing a detailed explanation of the aggregate difference in means. Also, following Jann (2008), individual standard errors may be obtained for inference.

4. EMPIRICAL RESULTS

4.1 Benchmark Model

The dependent variable is residential mortgage loans. The initial benchmark model consists of the estimation of equation (1) with one bank-specific and two economy-specific control variables: deposits, the interest rate, and the domestic stock price index. Deposits and the domestic stock price index are measured in real terms (deflated by the consumer price index) and transformed to logs, while the interest rate is in nominal terms. Traditional regression analysis based on OLS can be particularly sensitive to outliers, as discussed in the previous section. Although asymmetry seems not to be as problematic as outliers may be, large skewness can also compromise the least squares results. Therefore, skewness and kurtosis of the residuals are reported at the bottom of each table. The significance level of the null that skewness is equal to

[9] Another widely used approach is the two-fold decomposition, where the difference in mean has an explained and unexplained component. Results in this paper follow the threefold decomposition; however, results for the twofold decomposition are available upon request. The difference in interpretation of the results is not large.

zero while kurtosis is equal to three, reference magnitudes for the normal distribution, have also been included for these two statistics.

The logarithmic transformation may mitigate the effect of the large number of outliers in the right side of the distribution, as well as its skewness, for variables such as mortgage loans, deposits, and the stock price index, but also for other variables to be considered later (such as gross domestic product [GDP])[10]. However, it may only be partially successful, as suggested by the large kurtosis and skewness of our least square results later, especially with a large number of outliers. Therefore, an alternative estimator is considered—the robust MM-estimator described in the previous section with good breakpoint and efficiency levels. In the context of panel data, our MM-estimator copes well with the existence of clusters of outliers which may affect the results in two particular situations: (i) when all observations of a particular bank may be considered outliers; or (ii) when an outlier of an economy-specific variable in a particular year may affect a large number of banks.

Table 5 shows the initial estimates where year dummy variables were included in all cases to control for year effects (coefficients not reported). The first two columns show the basic model without the LTV variable. Columns (3)–(4) and (5)–(6) include economy and bank fixed effects, respectively. Columns (7) and (8) eliminate bank fixed effects by transforming all variables to first differences. Results from least squares are given in the odd columns while the even columns present the results from the MM-estimator. The analysis of the skewness and kurtosis of the residuals shows the improvements in the residuals from the MM-estimator. This is especially true when introducing the first difference transformation in (8) since either skewness or kurtosis tend to be larger when considering economy (4) and bank (6) fixed effects. In the case of several alternative specifications with bank fixed effects as in (6), the kurtosis is always larger than when considering an alternative specification in first differences as in (8).[11]

This is consistent with the proportion of observations that were assigned a weight of zero (i.e., equivalent to being excluded from the regression) and a weight below 0.5, which is a low weight, at the bottom of the table and the histograms in Figure 1 with the full distribution of the weights. The first-difference transformation shows a larger proportion of weights away from zero and closer to one than the two fixed effects specifications. Bank fixed effects seem to be particularly problematic, with almost 30% of the distribution at the zero lower bound. These numbers show the MM-estimator found a large number of outliers, much larger than what is usually considered in applied work, if we compare these numbers with the usual practice of trimming, at most, 10% (5% from above and 5% from below) of the observations. Given the degree of outlier contamination, any other estimator with a low breakdown point would probably perform badly.

Based on our first-difference specification, the last two columns present the most interesting results. This is the estimation of equation (2) with variables in first differences, the LTV variable and time fixed effects. The LTV dummy variable is statistically significant and negatively correlated with mortgage loans. Our results confirm the hypothesis that LTV caps reduce the growth of mortgage loans, which may have a positive impact on macroeconomic stability. In Table 4, the robust mean of the residential mortgage loan growth rate is 7.8%. The magnitude of the coefficient in column (10) would imply that, on average, mortgage loans would grow 7.3% per year

[10] However, logs would make the problem worse in the opposite case (i.e., variables with high kurtosis and skewed to the left), such as house prices and exchange rates.

[11] These additional specifications are not presented here, but are available by request.

slower in economies with an LTV cap policy. It is important to make the comparison relying on robust estimators and robust means. While the residential mortgage loan growth rate robust mean is 7.8%, the classic mean is 16.2%. Comparing columns (9) and (10), one plausible interpretation is that, if outliers were not addressed, OLS results would have overestimated the slower growth rate by 8.4 percentage points, which is a very large number, because of the presence of very large outliers in the right tail of the distribution.

Table 5: Least Squares Regression vs Robust Regression Comparison

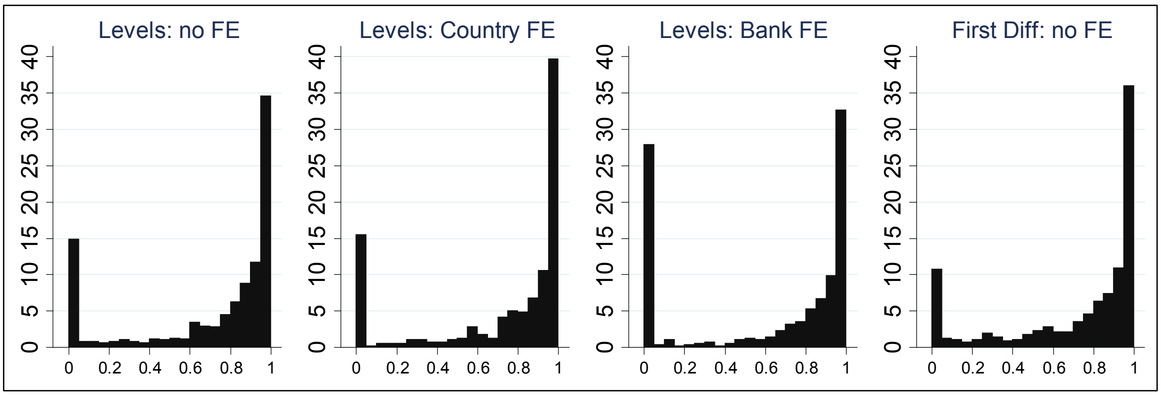
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Customers' deposits	1.113***	1.030***	1.110***	1.025***	0.740***	0.631***	0.734***	0.585***	0.697***	0.555***
	(0.062)	(0.017)	(0.066)	(0.020)	(0.161)	(0.075)	(0.164)	(0.075)	(0.162)	(0.070)
Interest rate	-0.056	-0.116***	0.064	0.081***	0.069***	0.031**	0.009	0.012	0.008	0.011
	(0.038)	(0.016)	(0.050)	(0.030)	(0.027)	(0.014)	(0.018)	(0.010)	(0.018)	(0.010)
Stock price index	-1.335***	-0.965***	0.153	-0.115	0.479**	-0.419	0.406**	0.191***	0.344**	0.171**
	(0.218)	(0.085)	(0.334)	(0.185)	(0.196)	(0.573)	(0.179)	(0.073)	(0.170)	(0.069)
Loan-to-value ratio									-0.148***	-0.072***
									(0.032)	(0.016)
Constant	-3.843***	-2.369***	-5.238***	-3.835***	-4.684***	-3.464***	-0.012	-0.048*	0.003	0.007
	(0.819)	(0.247)	(1.108)	(0.360)	(1.147)	(0.513)	(0.048)	(0.027)	(0.046)	(0.027)
Observations	780	780	767	767	780	780	567	567	567	567
Fixed effects	no	no	economy	economy	bank	bank	no	no	no	no
First differences	no	no	no	no	no	no	yes	yes	yes	yes
Residuals—Summary Statistics										
Standard Error	1.276	0.454	1.232	0.368	0.343	0.0544	0.428	0.114	0.425	0.111
Skewness	-0.530***	-0.246***	-0.291***	-0.239**	-0.177**	-0.160	6.077***	0.0654	6.129***	0.0764
Kurtosis	14.02***	3.154	15.60***	3.302	21.44***	3.561	82.85***	3.261	84.18***	3.292
weight = 0		96		124		215		46		50
(% of Obs)		(12%)		(16%)		(28%)		(8%)		(9%)
weight < 0.50		175		189		257		124		128
(% of Obs)		(22%)		(25%)		(33%)		(22%)		(23%)

Obs = observations.

Notes: Regressions (1), (3), (5), (7), and (9) are OLS, while (2), (4), (6), (8), and (10) are MM-robust. All regressions include year fixed effects. Standard errors in parentheses. The individual coefficient statistical significance level are: *** p<0.01, ** p<0.05, * p<0.1. Likewise, the skewness and kurtosis statistics significance levels are 1%, 5%, and 10%, where the null hypothesis in each case is a skewness of zero and a kurtosis of three, respectively.

Source: Authors' estimates.

Figure 1: Distribution of Weights—Residuals



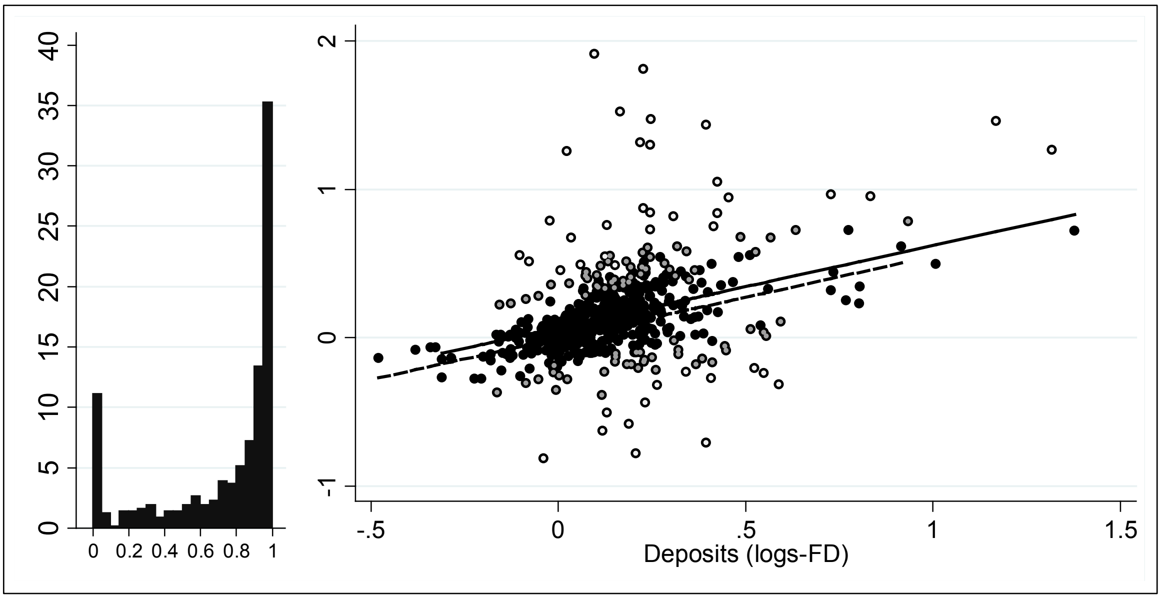
First Diff = first difference; FE = fixed effects.

Notes: The weight of an observation is its measure of outlierness. The four histograms depict the distribution of the weights from regressions (2), (4), (6), and (8), respectively. They have been scaled to percentages. Notice the bin width is 5%, so the first bar to the left (0%–0.05%) is not the percentage of observations with weight zero from Table 1 (but close).

Source: Authors' estimates.

The distribution of the weights in regression (10) can be found in Figure 2, which is very similar to that of regression (8). The scatterplot shows how observations are treated by the MM-estimator. Observations farther away from the regression line are the outliers, with some of them being quite far away. The distance between the solid line and the dotted line is –0.073, which is the coefficient of the LTV variable. This is not a small magnitude, since it implies a 7.3% change; however, the plot would suggest it is not that large since the range of y-axis is from –1 to 2. This is because of the extremely large magnitudes in mortgage loan growth experienced by Asian banks. Hollow dots are the most extreme observations which were assigned a weight of zero while most observations are depicted by solid black dots with a weight larger than 0.5. However, the scatterplot in Figure 2 should be interpreted with some care. Outliers are identified by their weights, a measure that relies on all the dimensions of the data sets and not only in the two dimensions plotted here. It is entirely possible that an observation is considered as an outlier (i.e., a low weight) although it may lie close to the regression line in Figure 2 if the outlierness is due to some other characteristic of the data (e.g., a rare magnitude in either the interest rate or the stock price index).

Figure 2: Outliers and LTV



LTV = loan-to-value; FD = first difference.

Notes: The histogram on the left shows the distribution of the weights of regression (10). The scatterplot on the right depicts the regression lines when LTV=0 (solid line) and LTV=1 (dashed line) from regression (10). There are three types of observations according to their outlierness: a) hollow dots with a weight of 0 (42 obs), b) grey dots with positive weights below 0.5 (86 obs), and c) solid black dots with weights above 0.5 (441 obs). The eight most extreme outliers were excluded fom the scatter plot to make the remaining observations easier to see.

Source: Authors' estimates.

4.2 Alternative Specifications

Tables 6 and 7 expand the set of controls to be considered to test whether the results for LTV are robust to alternative specifications. Table 6 considers additional variables from an open economy perspective: current account balances, exchange rates, and interest rate differentials. Some theoretical foundations to justify the introduction of these variables may be found in the uncovered interest parity (UIP) theory and the integration of small economies into the international capital markets and hence their links to the domestic housing market. Exchange rates and persistent current account imbalances may have an impact on the financial sector, including mortgage loans. For example, Cuestas and Staehr (2014) found a strong macroeconomic association between domestic credit creation and capital inflows when looking at some peripheral European Union (EU) countries. They conclude that capital inflows have been an important source of funds to fuel the credit booms in most of those countries.

Table 6: Open Economy Specifications

	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Customers' Deposits	0.555***	0.552***	0.510***	0.509***	0.515***	0.510***	0.515***
	(0.070)	(0.070)	(0.060)	(0.060)	(0.071)	(0.060)	(0.071)
Interest Rate	0.011	0.011	0.013	0.015			
	(0.010)	(0.010)	(0.009)	(0.009)			
Stock price index	0.171**	0.176***	0.179***	0.175***	0.186***	0.179***	0.186***
	(0.069)	(0.067)	(0.067)	(0.067)	(0.069)	(0.067)	(0.069)
Loan-to-Value ratio	-0.072***	-0.071***	-0.052***	-0.053***	-0.053***	-0.052***	-0.053***
	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)
Current Acc. (% GDP)		0.001					
		(0.003)					
Exchange Rate, Real			-0.645***	-0.614***	-0.622***	-0.645***	-0.622***
			(0.205)	(0.211)	(0.201)	(0.205)	(0.201)
Real Exch Rate, St Dev				-0.348			
				(0.473)			
Interest Rate, real					-0.001		
					(0.004)		
Interest Rate Differential						0.013	
						(0.009)	
Interest Rate Diff., Real							-0.001
							(0.004)
Constant	0.007	0.050	0.005	0.034	0.030	0.037	0.025
	(0.027)	(0.030)	(0.026)	(0.026)	(0.026)	(0.027)	(0.026)
Observations	567	567	567	567	567	567	567
St. Deviation (residuals)	0.111	0.111	0.107	0.107	0.107	0.107	0.107
Skewness (residuals)	0.076	0.073	0.124	0.129	0.127	0.124	0.127
Kurtosis (residuals)	3.292	3.284	3.299	3.298	3.275	3.299	3.275
weight = 0	50	51	57	58	58	57	58
(% of Obs)	(9%)	(9%)	(10%)	(10%)	(10%)	(10%)	(10%)
weight < 0.50	128	129	130	132	133	130	133
(% of Obs)	(23%)	(23%)	(23%)	(23%)	(23%)	(23%)	(23%)

Notes: See notes in Table 5.

Source: Authors' estimates.

We consider bilateral exchange rates (with the US dollar) in real terms where an increase in the exchange rate is a depreciation of the currency. The negative sign may indicate that a depreciation of the currency (i.e., an outflow of capital from the domestic economy) has a negative impact on the mortgage loan market. This sign is expected; however, it is surprising the current account is not statistically significant since both variables intend to capture the same effect of capital inflows/outflows.

Also, alternative proxies of interest rates do not change the fact that the interest rate seems not to be statistically significant, as in Table 5. One possible interpretation of the significant negative sign of the exchange rate relates to how it affects the relative returns of assets across economies. Although interest rate differentials seem not to affect decisions in the mortgage loan market, the exchange rate does. A depreciation of the national currency may discourage investment in the housing market because investment abroad becomes more attractive. This interpretation is in line with the uncovered interest rate parity condition in international macroeconomics models. Also, it would be consistent with the non-significance of the current account. While regression (11) suggests the capital outflows experienced in the region have not had a negative impact on mortgage loan growth; the negative sign of exchange rates would imply that the general trend of real exchange rate appreciation of most Asian currencies has made investment in their housing markets more attractive, encouraging the growth of mortgage loans.

Table 7 adds other economy-specific variables (GDP, house prices, inflation, expectations about GDP and inflation, and presence or absence of mortgage insurance policy[12]) and bank-specific variables (nonperforming loans, liquid assets, and core–noncore business ratio), departing from specification (12) in Table 6 (i.e., exchange rates are now included in the model). Surprisingly, the interest rate is still not significant most of the time. Among the new variables, GDP, house prices, and liquid assets are consistently statistically significant. In particular, GDP and house prices may be of special interest because of their policy implications. House prices are probably a key factor for the risk of financial crises. Other things equal, a larger negative reaction in mortgage loans with higher house prices would be expected, since house prices may be an indicator of the riskiness of the housing market: low prices would indicate favorable conditions to enter the market, while high prices may convince some buyers to take a more conservative approach.[13] Ceteris paribus, the expected sign on the coefficient of GDP is positive since this variable may be an indicator of the general economic conditions in the economy: in an environment with favorable economic conditions, people would be more willing to invest in the housing market. Finally, liquid assets are also statistically significant (but only at the 10% level). A priori, the negative sign is contrary to our expectations since banks with more liquid assets would be in a better position to provide mortgage loans. Other bank-specific characteristics seem not to have an effect on mortgage loans, including non-performing loans, which may be critical for the financial stability of the bank. We expected mortgage insurance policy to have positive effects on loans, as the existence of this policy would transfer the risk of loss from property owners to an insurance company, which would incentivize property owners to take more loans. However, the coefficients are not significant although they have the expected sign.

[12] Mortgage insurance policy is a dummy variable constructed to reflect whether this policy has been implemented in a particular economy and year, based on individual central bank information.

[13] On the contrary, a positive association would be expected if there were a housing bubble where high house prices are a signal of even higher house prices in the future.

Table 7: Additional Control Variables

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Customers' deposits	0.421***	0.418***	0.401***	0.420***	0.421***	0.445***	0.478***	0.449***
	(0.064)	(0.081)	(0.096)	(0.076)	(0.081)	(0.064)	(0.046)	(0.072)
Interest rate	0.008	0.016*	0.017*	0.018*	0.016*	0.017*	0.017**	0.018**
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
Stock price index	0.139**	0.106	0.113*	0.101	0.102	0.085	0.078	0.113*
	(0.067)	(0.064)	(0.066)	(0.063)	(0.066)	(0.063)	(0.060)	(0.063)
Real exchange rate	-0.635***	-0.728***	-0.634***	-0.702***	-0.765***	-0.792***	-0.707***	-0.800***
	(0.227)	(0.235)	(0.233)	(0.240)	(0.237)	(0.197)	(0.208)	(0.216)
Loan-to-value ratio	-0.055***	-0.050***	-0.052***	-0.048***	-0.056***	-0.039**	-0.045***	-0.051***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)	(0.016)	(0.016)
Real GDP (index)	1.195***	1.380***	1.480***	2.262***	1.329***	1.412***	1.408***	1.326***
	(0.223)	(0.281)	(0.304)	(0.749)	(0.269)	(0.248)	(0.248)	(0.273)
House Price		-0.175*	-0.191**	-0.163	-0.182**	-0.184**	-0.163*	-0.182**
		(0.090)	(0.086)	(0.100)	(0.092)	(0.084)	(0.085)	(0.087)
Inflation			-0.003					
			(0.003)					
Inflation, St. Dev.			-0.016					
			(0.015)					
GDP, expected				-0.729				
				(0.551)				
Inflation, expected				-0.011				
				(0.008)				
Mort. Insurance Pol.					0.014			
					(0.019)			
Non-perf. Loans (%)						-0.007		
						(0.008)		
Core/Noncore inc.							0.009	
							(0.028)	
Liquid assets (% dep)								-0.003*
								(0.002)
Constant	-0.041	-0.087***	-0.100***	-0.111***	-0.029	-0.107**	-0.064**	-0.032
	(0.028)	(0.032)	(0.038)	(0.041)	(0.033)	(0.051)	(0.028)	(0.042)
Observations	567	540	540	538	540	521	501	470
St. Deviation	0.100	0.0979	0.0981	0.0978	0.0966	0.0944	0.0939	0.0894
Skewness	-0.0155	0.0097	0.0390	-0.0247	0.0075	0.0196	0.0080	0.0097
Kurtosis	3.364	3.321	3.272	3.308	3.318	3.311	3.388	3.128
weight = 0	61	62	63	60	63	56	61	52
(% of Obs)	(10%)	(11%)	(12%)	(11%)	(12%)	(11%)	(12%)	(11%)
weight < 0.50	138	131	130	132	133	128	122	106
(% of Obs)	(24%)	(24%)	(24%)	(25%)	(25%)	(25%)	(25%)	(25%)

Dep. = deposits; GDP = gross domestic product; Inc. = income; Mort. Insurance Pol. = mortgage insurance policy; Non-perf. Loans = non-performing loans; St. Dev. = standard deviation.

Notes: See notes in Table 5.

Source: Authors' estimates.

4.3 Loan-to-Value Effects: Nonlinearities

Table 8 shows the regressions including interaction effects between LTV and other explanatory variables. From Table 6, the real bilateral exchange rate is considered together with the most significant variables from Table 7. Regression (25) considers all the variables from the benchmark model: the exchange rate, GDP, house prices, and liquid assets, together with LTV and its interactions with all the other right-hand-side variables. Liquid assets become non-significant, but two of the interaction terms are now significant: the stock price index and the exchange rate. The direct effect of LTV (i.e., the coefficient of LTV) does not change much (from –0.051 to –0.048), but now it is statistically significant at only 10%. Regressions (26) and (27) consider each of the two LTV groups separately. The advantage of having separate regressions is that the interpretation of the coefficients of the right-hand-side variable is straightforward. However, the direct effect of LTV on mortgage loans needs to be computed as the difference in the constant terms of the regressions.

Table 8: Nonlinearities—LTV Iterative Terms

	(25)	(26)	(27)	(28)	(29)	(30)
Customers' deposits	0.499***	0.498***	0.363**	0.897***	0.893***	0.266
	(0.084)	(0.083)	(0.182)	(0.054)	(0.062)	(0.188)
Interest rate	-0.012	-0.012	0.013			
	(0.013)	(0.013)	(0.010)			
Stock price index	0.151**	0.153**	-0.219**	0.179***	0.181***	-0.226**
	(0.063)	(0.063)	(0.087)	(0.047)	(0.048)	(0.089)
GDP	0.747**	0.755**	0.891**	0.389	0.390	0.911***
	(0.362)	(0.356)	(0.382)	(0.270)	(0.284)	(0.344)
House price	-0.165*	-0.166*	-0.042	-0.270***	-0.274***	-0.009
	(0.099)	(0.099)	(0.103)	(0.083)	(0.084)	(0.089)
Liquid assets	-0.001	-0.001	-0.003*			
	(0.004)	(0.004)	(0.002)			
Exchange rate	-0.539***	-0.537***	-1.172***	-0.083	-0.079	-1.074***
	(0.174)	(0.175)	(0.239)	(0.164)	(0.164)	(0.248)
Loan-to-value ratio	-0.048*			-0.056***		
	(0.025)			(0.021)		
LTV x deposits	-0.137			-0.625***		
	(0.207)			(0.186)		
LTV x interest rate	0.025					
	(0.017)					
LTV x stock price index	-0.366***			-0.402***		
	(0.107)			(0.099)		
LTV x GDP	0.143			0.528		
	(0.529)			(0.436)		
LTV x house price	0.121			0.258**		
	(0.143)			(0.121)		
LTV x liquid assets	-0.002					
	(0.004)					
LTV x exchange rate	-0.626**			-0.987***		
	(0.294)			(0.296)		
Constant	0.016	0.017	-0.032	0.032**	0.032**	-0.024
	(0.016)	(0.016)	(0.020)	(0.013)	(0.013)	(0.017)
No. observations	470	214	256	540	250	290
St. deviation (residuals)	0.0953	0.103	0.0967	0.101	0.110	0.104
Skewness (residuals)	0.0733	0.0118	0.0144	0.0409	-0.0257	0.0577
Kurtosis (residuals)	3.079	2.985	3.117	3.344	3.122	3.268
weight = 0	42	39	47	60	58	64
(% of Obs)	(9%)	(18%)	(18%)	(11%)	(23%)	(22%)
weight < 0.50	97	108	121	127	139	150
(% of Obs)	(21%)	(50%)	(47%)	(24%)	(56%)	(52%)

LTV = loan-to-value; No. Observations = Number of observations; Obs = observations; St. Deviation = standard deviation.

Notes: See notes in Table 5.

Source: Authors' estimates.

Regression (28) drops two variables that were not significant in (25), while regressions (29) and (30) consider LTV groups 1 and 2 separately again. In regression (28), LTV is significant at 1% again with a coefficient of –0.056 and all the interaction terms are significant at least at 5%, except for GDP. The comparison of regressions (29) and (30) suggests LTV has a clear influence on the importance of the other determinants of mortgage loans. In economies where LTV policies are imposed, house prices (our proxy for house market conditions) become insignificant, as well as deposits, which is the variable in our sample most closely related to the credit cycle. However, the opposite seems to be the case regarding macroeconomic conditions: both GDP and the exchange rate were not significant when LTV=0, but become significant if LTV policy is adopted. Higher economic growth and exchange rate appreciation seem to encourage mortgage loans. Lastly, the stock price index changes sign when LTV=1. When the government implements LTV, this change in sign may indicate that the housing market is overheating. The overheating of the housing market may create fear in the market of bubbles being formed, thereby impacting the stock market negatively.

4.4 Blinder-Oaxaca Decomposition

Finally, Table 9 presents the Blinder-Oaxaca decomposition analysis, considering both the full model and the more restrictive model without the interest rate and liquid assets. The full model is based on regressions (26) and (27) and there is a significant difference of 5.2 percentage points between the two groups: mortgage loans grow at 11.7% in economies without LTV policy, while economies that have adopted LTV policies grow at 6.5% on average. The threefold decomposition shows the difference in means may be explained mostly by differences in the coefficients of the regression, mainly the LTV dummy,[14] which explains a difference of 4.9 percentage points (significant at 10%). We fail to identify other significant differences, except for some smaller effects of endowment differential of GDP and coefficient difference in the coefficient of exchange rates. The stock price index displays significant effects in its three components (endowment, coefficients, and their interaction) but they seem to cancel each other out.

Once the interest rate and liquid assets are removed, the Blinder-Oaxaca decomposition based on regressions (29) and (30) shows a similar story, but some of the other variables now play a bigger role. The average growth rate of mortgage loans in LTV economies is 8.1 percentage points lower than for non-LTV economies, and this difference is mainly explained by differences in the coefficients of the two regression lines (7.7 percentage points). Again, the LTV dummy is important to explain the difference in coefficients of the two groups (and significant at 1% rather than 10% now), but the coefficient on deposits is also important in magnitude and significant. The magnitude of the difference of these two coefficients is so important that it offsets some differences in the opposite direction that are also significant but smaller (house prices and exchange rates mainly). This effect suggests LTV policies are associated with a reduction of the effect of booms in credit creation in the mortgage market, which would be an important outcome for economic policy. The endowment effect of GDP is also significant and opposite in sign. The stock price index is the only variable that shows significant effects of the three different types of effects but they cancel each other out, again.

[14] This is the difference in the constant of the regression between the two subsamples.

Table 9: The Blinder-Oaxaca Decomposition of the Effect of LTV

Group Means:						
LTV=0 (group 1)		0.117***			0.148***	
		(0.018)			(0.016)	
LTV=1 (group 2)		0.065***			0.067***	
		(0.014)			(0.013)	
Difference		0.052**			0.081***	
		(0.023)			(0.021)	
	endowm.	coeff.	interac.	endowm.	coeff.	interac.
Overall	0.010	0.056**	-0.014	0.017	0.077***	-0.013
	(0.015)	(0.022)	(0.014)	(0.013)	(0.018)	(0.015)
Deposits	0.006	0.013	0.002	0.006	0.062***	0.014
	(0.007)	(0.020)	(0.004)	(0.006)	(0.021)	(0.011)
Interest rate	-0.006	-0.001	0.011			
	(0.005)	(0.002)	(0.008)			
Stock price index	0.016**	0.019***	-0.027**	0.017**	0.019***	-0.031***
	(0.008)	(0.007)	(0.011)	(0.008)	(0.006)	(0.011)
GDP	-0.018**	-0.009	0.003	-0.016**	-0.034	0.009
	(0.008)	(0.034)	(0.010)	(0.007)	(0.029)	(0.008)
House price	0.001	-0.006	0.002	0.000	-0.012**	0.003
	(0.002)	(0.007)	(0.003)	(0.001)	(0.006)	(0.003)
Liquid assets	-0.000	0.000	0.000			
	(0.002)	(0.001)	(0.001)			
Exchange rate	0.011	-0.009**	-0.006	0.010	-0.014***	-0.009
	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
LTV rat.		0.049*			0.056***	
		(0.025)			(0.022)	

LTV = loan-to-value; GDP = gross domestic product.

Notes: All variables are in first differences. Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

5. CONCLUSIONS

Ours is the first paper we are aware of that measures the effects of loan-to-value (LTV) on mortgage loans, the direct target of LTV policy. Moreover, the paper estimates the micro-level impact by using data on individual banks in Asia. The estimation of the mortgage loan equation shows there is a strong economic effect of LTV ratio policies. However, our work shows that the correct estimation of this effect requires taking into account the presence of outliers, which is a real concern in our sample where bank-specific data can have a large number of outliers. The MM-estimator used in this study is well suited to deal with outliers by making use of weights. The MM-estimator suggests around 25% of the sample needs to be downweighted at least by half compared with ordinary least squares, and around 10% of the values are so extreme that they should be disregarded (i.e., assigned a weight of 0). Estimators highly sensitive to a large presence of outliers (i.e., low breakdown point) would probably perform badly.

LTV is one of a handful of variables that help to explain mortgage loans. The other variables that are consistently significant are deposits, the stock price index, gross domestic product, house prices, and exchange rates. The impact of the LTV variable also seems to be large when compared to the other determinants. When a robust-to-outliers estimator is used, the growth rate differential of economies with and without LTV policies is 8.1 percentage points, with 5.6 percentage points of that reduction explained by the direct effect of LTV policies on the mortgage market. This 5.6

percentage point difference is not only a statistically significant effect, but also quite large in magnitude. LTV has also some indirect effects through its impact on coefficients of the other determinants of mortgage loans—bank deposits in particular.

This study focuses on the relevance of LTV policy in the mortgage market given the large magnitude of loan growth observed in the individual bank data in Asian economies. The mortgage market has been expanding rapidly, especially in some of the countries of the region—the People's Republic of China, Malaysia, and Thailand—and two-digit growth in mortgage loans is not rare. Having a tool to effectively regulate their expansion is at the core of the concerns of financial stability policymakers in the region.

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