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Economic Research Department
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The views expressed in this paper are those of the authors and do not necessarily reflect the official view of the Magyar Nemzeti Bank.

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## Abstract

Housing market is important from a macroprudential perspective because it has a strong effect on the banking sector. Changes in real estate prices may affect the level of bank risk through household mortgage lending, however, the literature has no clear conclusion on this impact mechanism. Using a bank-level database containing quarterly data from 1998 to 2016 we estimated dynamic fixed-effects panel models to examine how bank risk is influenced by housing prices via mortgage lending in the Hungarian banking system. According to the results (1) higher house prices lead to higher bank risk, (2) the higher the share of mortgage loans at a bank, the stronger the positive effect of house prices on bank risk. In the period following the onset of the crisis a much stronger positive relationship could be observed between house prices and bank risk than before the crisis. Using the house price gap which measures the deviation of house prices from their fundamental value we provide empirical evidence that the deviation hypothesis was stronger for Hungary. This suggests that both banks and households tend to undertake excessive risks during a housing market boom, which can be mitigated by macroprudential policy instruments.


**Keywords:** bank risk, house price index, mortgage loan, real estate market

**JEL Codes:** G21;G28; G30; C23

# 1. Introduction

Housing market has a strong effect on the economy as a whole. As residential property is the main asset of Hungarian households, consumption and saving decisions are strongly influenced by house prices. In the corporate sector, property prices and number of transactions influences demand for new investments, and ultimately has an effect on the construction industry and its suppliers.

This strong effect also appears in the banking sector. The performance of mortgage loans, which account for a major portion of household loans, is determined by the property market in several respects. A decline in house prices causes banks' expected loan losses to increase for two reasons: (1) the value of collateral decreases, which raises the loss given default (LGD); and (2) the probability of default (PD) increases as it becomes less worthwhile for the borrower to continue servicing the debt. In the corporate sector, a decline in property prices may have a negative effect through the construction industry in particular, because it lowers the number of investments and the profitability of construction firms, which ultimately also has a negative effect on the performance of bank exposures related to the real estate sector. These factors affect both capital position and P&L through impairment, eroding the stability of financial institutions. Conversely, when property prices rise, the exact opposite may occur, strengthening banks' positions. Moreover, rising real estate prices support the launch of new investments and lead to stronger bank activity, which, *inter alia*, can improve profitability and help to maintain a low NPL ratio, i.e. reinforce institutional stability.

Apart from the obvious impact mechanisms mentioned above, rising property prices can also increase risks. Higher house prices make property purchases more attractive, while also motivating banks to lend more actively. One possible result can be that the banking sector serves increasingly poor quality borrowers by selling increasingly risky loan products, as shown by the example of the US subprime market. It should be noted that foreign currency lending in Hungary also exhibited these features in 2007–2008 (Balás et al., 2015). Additionally, with a rapid rise in house prices, banks which are active in mortgage lending become more exposed to a potential downturn in the property market, possibly posing a major risk to bank stability, particularly when this is associated with high indebtedness among borrowers.

Our study identifies the effect of house prices on bank stability and examines whether the size of the effect depends on banks' exposures to the housing market. This question is highly relevant in terms of policy, as the macroprudential toolkit includes several instruments that can be used to mitigate risks related to the real estate market. For example, implementation of sector-specific macroprudential rules (i.e. higher risk weights or minimum LGD values for portfolios with real estate collateral; ESRB 2016) may help to mitigate the vulnerability of the banking sector, when risks of banks with larger housing market exposures increase at a relatively faster rate than the increase in house prices.[1]

Analyses of the effect of house prices on bank risks have the same dual nature as described above. Studies report varying results on the interaction of house prices – or more broadly, mortgage lending – and risks. Although Blasko and Sinkey's (2006) study of the US banking sector was not directly focused on house prices, its findings on the interaction between intensifying mortgage lending and bank risks are relevant for us. The authors analysed the entire banking sector over the period between 1989 and 1996 and found that regulations increasingly pushed banks towards mortgage lending, because that was considered to be the least risky. As a result, however, banks which engaged more actively in mortgage lending became relatively risky. By contrast, less specialised institutions demonstrated better stability in the period under review. However, that finding does not necessarily derive from the higher risk of mortgage loans; it is possible that the relative safety of mortgage loans encourages banks to take more risk. Koetter and Poghosyan (2010) specifically examined the direct effect of house prices on bank risk. The authors tested two hypotheses on the relation between the German banking sector and the real estate markets of various regions. Their results failed to confirm the *collateral value hypothesis*, i.e. rising house prices reduce bank risks due to more favourable LGD and PD levels. Conversely, they showed that the *deviation hypothesis* could be accepted, i.e. that deviation from the equilibrium value increased bank risks. Somewhat in contrast to these findings, Gibilaro and Mattarocci (2016) examined a broader international sample and demonstrated a clearly positive correlation between house price levels and bank stability, as measured by the Z-risk indicator. They found that rising house prices improved banks' profitability and capital position. Importantly, however, the authors found that this positive effect only applied to banks which were not specialised in household mortgage lending. With banks engaged in mortgage lending, no causal relationship could be shown between house prices and Z-risk, because that risk is probably better managed by specialised institutions. Following the approach of Gibilaro and Mattarocci (2013), Rebi (2016) performed a similar analysis of the Albanian banking sector and found that banks with higher mortgage loan ratios seem to be riskier through their relatively larger exposure to housing

[1] Restrictions on the loan-to-value, loan-to-income and payment-to-income (LTV, LTI and PTI) indicators, which are now used quite widely, affect banks' new lending. Therefore, such restrictions are mainly suitable to alleviate the further accumulation of risks rather than to mitigate risks from existing exposures.

market developments. Empirical results show that rising house prices mitigate the risk of so-called "non-real estate" banks (which had a ratio of mortgage loans of less than 20 per cent in five consecutive years), while leading to higher riskiness in the case of "real-estate" banks.

Literature shows considerable variations in terms of methodology, and conclusions also differ occasionally. Koetter and Poghosyan (2010) underline that the results may depend strongly on the housing market on which the hypotheses are tested, given that e.g. imbalances were significantly more limited in the German housing market compared to the US or Spanish markets.

Several key issues arise based on the literature with a potentially significant effect on results. In our paper we investigate the relationship of bank risk and real estate prices with strict focus on essential issues suggested by the existing literature. (1) A fundamental question suggested by Gibilaro and Mattarocci (2016) is whether the institution concerned is specialised or not, for which we control in our analysis. (2) Koetter and Poghosyan (2010) demonstrated that the level of house prices and deviation of house prices from the equilibrium may produce different effects. In our study, we consider both approaches in order to develop a better understanding of the effect of the real estate market. (3) We find that the method of measuring risk is also relevant. While studies generally use the Z-risk indicator (Rebi 2016, Blasko and Sinkey 2006, Gibilaro and Mattarocci 2016) as dependent variable, Koetter and Poghosyan (2010) measure bank risk with a probability of bank default indicator. In our research, we also test the influence of the risk indicator on the result, i.e. the extent to which the effect measured depends on the definition of bank risk.

It should also be pointed out that most studies examine the household and corporate sectors jointly. We do not consider this expedient for two reasons. First, lending is often significantly different in the household and corporate sectors: for example, in Hungary before the onset of the crisis, the estimated size of the credit gap in the market for household loans was 1.5 times that of the corporate market (Hosszú et al., 2014). Second, there may be significant difference in the risk of the residential and commercial property markets. Developments in the housing and commercial property markets may affect bank stability in different ways. As our research is focused exclusively on the housing market, we use a house price index to capture developments in the real estate market, while using banks' exposure to the household mortgage loan market to measure their relationship with the property market.

Section 2 of the paper describes the data used, while Section 3 set out the methodology applied. The results are presented in Section 4. A detailed robustness test is performed in Section 5. A conclusion based on our findings is provided in Section 6.

## 2. Data

In our study, we used a unique bank-level database containing Hungarian banks present in the Hungarian banking market since late 1998, which were active in mortgage lending (i.e. the observation period included sections where the bank concerned reached a market share of at least 1 per cent). Ultimately, 13 banks were included in the sample, which contains quarterly data from 1998 Q4 to 2016 Q2. Specific bank characteristics were merged with macroeconomic variables, also measured on a quarterly basis. The descriptive statistics on the variables presented in the following are included in *Table 5* in the Annex.

Our dependent variable is a bank risk indicator which is compiled closely following the approach used by the EBA (EBA 2015) for deposit guarantee purposes.[2] The risk indicator contains six bank characteristics (*Table 1*), each assigned a risk rating between 0 and 100 based on thresholds defined for the Hungarian market, with higher values indicating higher bank risk. The bank risk indicator used as the dependent variable in our models is generated by aggregating the six risk indicators using the proportionately rescaled weights of the EBA guideline.

Although different types of Z-risk measures are commonly used in the literature as risk indicators, we decided to use this composite indicator containing information on several aspects of riskiness. While Z-risk focuses only on leverage and profitability, our measure has a broader perspective. As suggested by experiences from the global financial crisis (GFC), capital adequacy and asset quality are also important, considering the impact of a housing boom on liquidity. As Blasko and Sinkey (2006) suggested, a rise in house prices increases the risk-taking of banks. But this phenomenon is not necessarily reflected by the leverage. Moreover, taking a medium-term horizon this higher risk-taking may improve profitability with relatively stable leverage, but the riskiness of mortgages (e.g. high PTI, high LTV contracts, subprime borrowers, etc.) increases, as reflected by the capital adequacy. The kind of composite indicator we use provides a clearer picture of the riskiness of banks by containing information on riskiness from several different perspectives.

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[2] We modified the methodology proposed by the EBA in that we: (1) disregarded covered deposits for the calculation of the risk indicator which is only important for deposit insurance agencies, (2) included one liquidity indicator instead of LCR and NSFR ratios and proportionately modified the original weights. Precise LCR and NSFR data are not available for such a long observation period.

*Table 1: Components of the bank risk indicator*

| Bank characteristic | Variable | Definition | Weight |
|---|---|---|---|
| Capital | Leverage ratio | Regulatory capital / Total assets | 14% |
| | Capital adequacy ratio | Regulatory capital / Risk-weighted assets | 14% |
| Liquidity | Liquidity ratio | Liquid assets / Total assets | 29% |
| Asset quality | Non-performing loans ratio | Non-performing loans / Total loans | 22% |
| Business model, management | Riskiness of assets | Risk-weighted assets / Total assets | 10% |
| | Return on assets | Average Net income / Total assets | 10% |

To compare, we also estimate models with the Z-risk indicator, as it is applied broadly in the literature. The Z-risk indicator proposed by Lepetit et al. (2013) is calculated in the following manner:

$$Z\ risk_t = \frac{\mu_{ROA} + Capital_t}{\sigma_{ROA}}$$

where $\mu_{ROA}$ is the mean, while $\sigma_{ROA}$ is the standard deviation of the return on assets, both calculated over the full sample; and $Capital_t$ is the ratio of equity capital to total assets.

The significance of banks' activity on the mortgage loan market was tested in two ways. On the one hand, we used the share of mortgage loans within total loans as a continuous variable *('Mortgage Ratio'*), and on the other hand, a dummy variable was created, which takes the value of 1 for banks that are active in the mortgage loan market, i.e. mortgage loans represent at least 30% of their total loans *('Mortgage Ratio>30%')*. *Figure 6* in the Annex provides insight on the dynamics and distribution of banks' mortgage lending ratio in the Hungarian banking system.

The most important macro variable in the model is the house price index *('HPI')*, which is the main focus of our research. This variable was measured by the MNB real house price index (*Figure 5* in the Annex). For robustness tests, we also used the house price gap *('HPG')*,[3] which is the deviation of house prices from the level justified by fundamentals. As a macro-level control variable, for specific estimates we also used the annual growth rates of

[3] The house price gap is the average of the gaps derived as the difference between the MNB real house price index and the equilibrium house price levels obtained from various estimates (MNB, 2017, p.12).

GDP *('GDP (agr)')*, real disposable income *('Disp. Income (agr)')* and the short-term interest rate (3-month BUBOR, *'Interest Rate (agr)'*).

As bank-level control variables, the models included the capital adequacy ratio *('CAR')*, the ratio of liquid assets to total assets *('Liquid assets ratio')*, the ratio of non-performing loans *('NPL')*, the return on total assets *('ROA')* and the share of foreign funds within the balance sheet *('Foreign funds ratio')*.

## 3. Methodology

We examined the effect of the house prices and mortgage exposure on bank stability in the following dynamic fixed-effects panel model:

$$y_{it} = \gamma\, y_{i,t-1} + \beta' x_{i,t-1} + \varphi' c_{it} + \alpha_i + \eta_t + \epsilon_{it}$$

for i=1, …, N and t=1, …, T. $y_{it}$ is the dependent variable, $y_{i,t-1}$ is the lagged dependent variable, $x_{i,t-1}$ is the vector of the independent variables in our focus[4] (housing market exposure, house price index, and the interaction thereof), $c_{it}$ is the vector of bank characteristics included as control variables, $\gamma$ is the coefficient of the lag, while $\beta$ and φ are vectors of the coefficients relating to independent variables. $\alpha_i$ is the cross-sectional fixed effect, $\eta_t$ is the period fixed effect, $\epsilon_{it}$ is the idiosyncratic error term with $E(\epsilon_{it})$=0, $E(\epsilon_{it}\epsilon_{js})$= $\sigma_\varepsilon^2$ if j=i and t=s, otherwise $E(\epsilon_{it}\epsilon_{js})$= 0.

We opted for fixed-effect panel regression as we assume that developments in the dependent variable are unobservable and vary by bank.[5] The fixed-effect component ($\alpha_i$) used in the model controls for unobserved heterogeneity across banks that is constant over time. As the time-series dimension of our panel is long (66 quarters) and much larger than the cross-sectional dimension (13 banks), we used the within regression estimator. Driscoll–Kraay (1998) standard errors were calculated,[6] which are robust in terms of heteroskedasticity, higher orders of autocorrelation and cross-sectional dependence (Hoeche, 2007).

Including the lagged dependent variable as an independent variable can result in biased estimates if the time dimension of the database is small (Nickell, 1981).[7] As T=30 is a border-line case, when we run regressions on two subsamples (i.e. the period before and after the

[4] The quarterly lags of these variables are included in the model, as we doubt that their effect would appear simultaneously in the risk indicator. For example, although the GFC significantly changed the state of banks, it took several quarters before the negative effect was reflected by risk indicators.

[5] The assumption of the fixed effects method (FE) is that the unobserved variable and the independent variables are correlated. The null hypothesis on no correlation between the unobserved variable and independent variables is rejected on the basis of the Hausman test. Consequently, the estimation of the random effects model (RE) is inconsistent and biased, which confirms the selection of the FE method.

[6] We examined whether the usual assumptions of the FE method were satisfied. We carried out formal tests to determine whether (1) the error term of the model is homoscedastic, (2) the error terms are autocorrelated up to some lag, and (3) cross-sectional dependence is present in the database. Based on test results, the error terms are heteroscedastic and autocorrelated, but cross-sectional dependence is not present in the data.

[7] Nickell proved analytically that in case of dynamic panel models with individual fixed effects, the LSDV parameter estimation is biased and inconsistent The Nickell-bias is negligible in case of N < T and a relatively large time dimension, which is why we can use it for those estimations that apply to the whole period.

onset of the crisis), we use also an additional estimation method,[8] the corrected Least Squares Dummy Variable (LSDVC) estimation approach.[9] The LSDVC was defined by Kiviet (1995), who provided an approximate formula for the magnitude of the bias obtained by the standard LSDV approach, and then adjusted the LSDV parameter estimation result with the estimated bias. Bruno (2005) provided the generalised form of the approximation formula, defined by Bun and Kiviet (2003), applicable to unbalanced panels. This approach is asymptotically consistent even in the case of panels with small cross-sectional dimension, which is relevant for our pre/post crisis analysis.

[8] This estimation method has also a shortcoming: it assumes that there is no higher order autocorrelation.

[9] Often-used dynamic panel estimation methods, such as the Instrumental Variable (IV) approach, first proposed by Anderson and Hsiao (1982), and GMM-type estimation methods, such as the Arellano-Bond (1991) and Blundell-Bond (1998) methods, return an unbiased result only in the case of a large cross-sectional dimension (Baltagi, 2013).

## 4. Results

The key question addressed in this paper is how the riskiness of banks is influenced by housing prices via mortgage lending. In the initial specifications, we estimated the effect of the mortgage loan ratio (two measures were tested: '*Mortgage Ratio*' and '*Mortgage Ratio >30%*'), the house price developments ('*HPI*'), and their interaction on the level of banks' risk indicator for the period of 2000 Q1 – 2016 Q2 (*Table 2*).[10]

*Table 2: Initial estimation results*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Lagged Bank Risk | 0.402*** | 0.403*** | 0.386*** | 0.377*** | 0.367*** |
| | (0.0419) | (0.0415) | (0.0416) | (0.0420) | (0.0424) |
| Mortgage Ratio >30% | -0.868 | | -12.74*** | | |
| | (0.802) | | (3.241) | | |
| House Price Index (HPI) | 0.214*** | 0.216*** | 0.212*** | 0.218*** | 0.217*** |
| | (0.0209) | (0.0237) | (0.0208) | (0.0224) | (0.0220) |
| Mortgage Ratio | | -0.0140 | | -0.0724** | -0.396*** |
| | | (0.0362) | | (0.0351) | (0.0756) |
| Mortgage Ratio >30% * HPI | | | 0.104*** | | |
| | | | (0.0298) | | |
| Mortgage Ratio * HPI>110 | | | | 0.0834*** | |
| | | | | (0.0265) | |
| Mortgage Ratio * HPI | | | | | 0.00315*** |
| | | | | | (0.000611) |
| Bank controls | YES | YES | YES | YES | YES |
| Bank fixed effects | YES | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES | YES |
| Number of observations | 843 | 843 | 843 | 843 | 843 |
| Number of groups | 13 | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.604 | 0.603 | 0.610 | 0.610 | 0.614 |

Note: Regressions include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

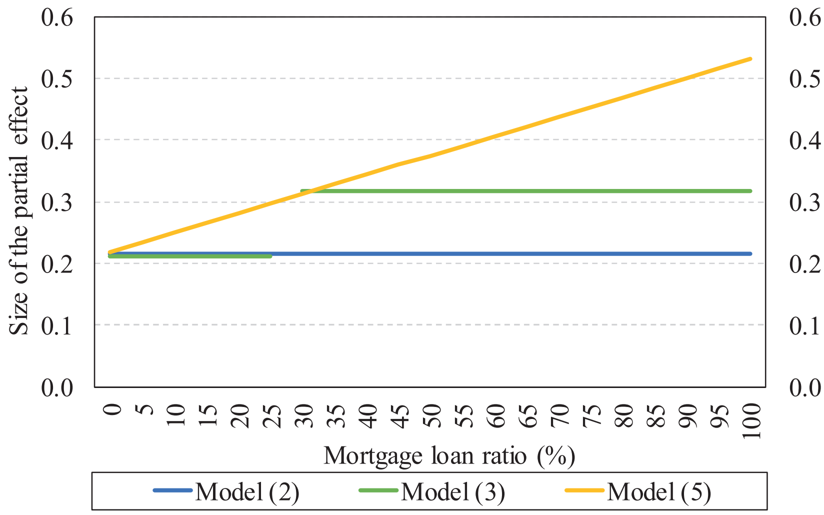
Apparently, the share of mortgage loans (either as a continuous variable or as a dummy) does not affect the level of bank risk in itself, but a strong positive connection is observed between

[10] In our estimates, we controlled for key bank characteristics such as profitability, portfolio quality, liquidity and solvency position. As a robustness test, we estimated the model by omitting bank control variables and it led to the same inferences.

house price dynamics and the level of bank risk. This positive relationship also holds when the interaction term is introduced into the model, whether the share of mortgage loans is added as a continuous variable or as a dummy.[11]

*Figure 1* shows the combined partial effect of the house price index which is positive in every specification, and thus higher house prices lead to higher bank risk. Moreover, the higher the share of mortgage loans at a bank, the stronger the positive effect of house prices on the risk level of that particular bank. Therefore, the estimation results support the *deviation hypothesis*, i.e. that banks tend to keep lending to increasingly risky customers as house prices rise, which increases their risks. Deteriorating quality of customers may be partly attributable to the fact that up to the onset of the crisis, banks allowed increasing levels of indebtedness (as found by Balás et al., 2015), and that the banking sector reached an ever wider customer base (Banai –Vágó, 2017).

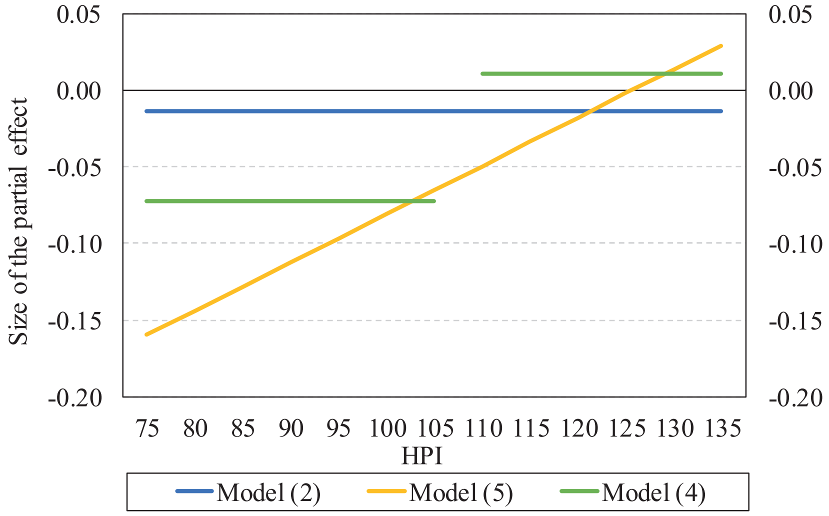
*Figure 1: Partial effect of house prices on bank risk (initial models)*




In addition to the size, the sign of the partial effect of the mortgage loan ratio, presented in *Figure 2*, also depends on the state of the housing market. In the case of relatively low house prices, if a bank has, *ceteris paribus,* a larger share of mortgage loans, its riskiness tends to be lower. However, in the case of relatively high real house prices, more intensive mortgage lending results in higher bank risk.

[11] In the following, therefore, the share of mortgage loans will only be used as a continuous variable.

*Figure 2: Partial effect of mortgage loan ratio on bank risk (initial models)*




In the above models, we used the first lag of the house price index, mortgage loan ratio and their interaction. This could influence our results. As outlined in the *collateral value hypothesis*, the positive effect of increasing house prices can appear in bank risks through credit risk indicators (PD, LGD), potentially resulting in a protracted house price effect. Depending on the bank, it was possible to review the collateral value of the properties securing the loans at intervals exceeding 1 year, and thus it is worth examining the effects of various lags of the housing market variables (*Table 3*).

Housing prices also seem to be strong risk drivers at lags of 2, 3 and 4 quarters, which is reinforced in all cases by a higher share of mortgage loans. However, the time profile of the effect differs between banks that are active in mortgage lending and banks that are less active. In the first case immediate effect is the strongest and subsequently diminishes, whereas in the latter the effect intensifies over time. This could be attributed to the fact that institutions focusing on mortgage lending respond to housing market developments faster and stronger, whereas others that are less active in this field only follow suit later.

*Table 3: Estimation results obtained using various lags*

| | (1)<br>1 lag | (2)<br>2 lags | (3)<br>3 lags | (4)<br>4 lags |
|---|---|---|---|---|
| Lagged Bank Risk | 0.367*** | 0.347*** | 0.343*** | 0.346*** |
| | (0.0424) | (0.0401) | (0.0408) | (0.0409) |
| House Price Index (HPI) | 0.217*** | -0.340*** | -0.244*** | -0.219*** |
| | (0.0220) | (0.0711) | (0.0753) | (0.0825) |
| Mortgage Ratio | -0.396*** | 0.209*** | 0.238*** | 0.235*** |
| | (0.0756) | (0.0222) | (0.0214) | (0.0227) |
| Mortgage Ratio * HPI | 0.00315*** | 0.00260*** | 0.00179*** | 0.00164** |
| | (0.000611) | (0.000604) | (0.000656) | (0.000719) |
| Bank controls | YES | YES | YES | YES |
| Bank fixed effects | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES |
| Number of observations | 843 | 842 | 841 | 840 |
| Number of groups | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.614 | 0.621 | 0.622 | 0.620 |

Note: Different lags of the main explanatory variables (Mortgage Ratio, HPI and Mortgage Ratio * HPI) are included in the models, according to the second line of the table. Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

Starting in Hungary at the end of 2008, the financial crisis may also have influenced the effect of house prices on bank risks. Although in our estimates the effect of the macro and institutional environments was taken into consideration through fixed period and bank effects, our results may be somewhat biased because of a structural break that potentially appears in the Hungarian time series. It is therefore important to examine the extent to which the above impact mechanism was altered by the crisis. Precisely for this reason, we performed separate estimates for the periods preceding and following the onset of the crisis (*Table 4*). Because of the shorter time dimension, we used two estimation methods[12] for these subsamples that led to almost the same inferences.

[12] The reason behind this is detailed in Section 3. Because of methodological difficulties due to the structure of our database, these results should be treated with care.

*Table 4: Estimation results for the periods preceding and following the onset of the crisis*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Estimator: | | Within | | | LSDVC | |
| Period: | Full | Pre-crisis | Post-crisis | Full | Pre-crisis | Post-crisis |
| Lagged Bank Risk | 0.367*** | 0.324*** | 0.281*** | 0.391*** | 0.381*** | 0.332*** |
| | (0.0424) | (0.0663) | (0.0703) | (0.0337) | (0.0452) | (0.0464) |
| House Price Index (HPI) | 0.217*** | 0.232*** | 0.319*** | -0.140 | -0.0673 | 0.935 |
| | (0.0220) | (0.0420) | (0.0522) | (0.538) | (0.414) | (0.626) |
| Mortgage Ratio | -0.396*** | -0.498* | -0.686*** | -0.391*** | -0.412** | -0.818*** |
| | (0.0756) | (0.259) | (0.138) | (0.116) | (0.207) | (0.197) |
| Mortgage Ratio * HPI | 0.00315*** | 0.00328* | 0.00315*** | 0.00308*** | 0.00274* | 0.00453*** |
| | (0.000611) | (0.00171) | (0.000848) | (0.000908) | (0.00153) | (0.00144) |
| Bank controls | YES | YES | YES | YES | YES | YES |
| Bank FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Observations | 843 | 453 | 390 | 843 | 453 | 390 |
| Groups | 13 | 13 | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.614 | 0.504 | 0.605 | - | - | - |

Note: "Pre-crisis" refers to the period preceding the onset of the crisis (2000-2008), while "Post-crisis" refers to the period following the onset of the crisis (2009-2016 Q2). Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

Our results show that in the period following the onset of the crisis a much stronger positive relationship could be observed between house prices and bank risk than in the period preceding the crisis. The effect was stronger in both periods in the case of those banks that were more active in mortgage lending (*Figure 3*).

The estimated partial effect of mortgage loan exposure is definitely negative in the case of the two subsamples, and thus *ceteris paribus* a higher mortgage loan ratio suggests lower bank risk (*Figure 4*). This risk-mitigating impact of stronger mortgage lending activity is larger in the case of a relatively low house price environment in both periods, and it seems to be substantially stronger in the period after the onset of the crisis.

*Figure 3: Partial effect of house prices on bank risk (before and after the crisis)*

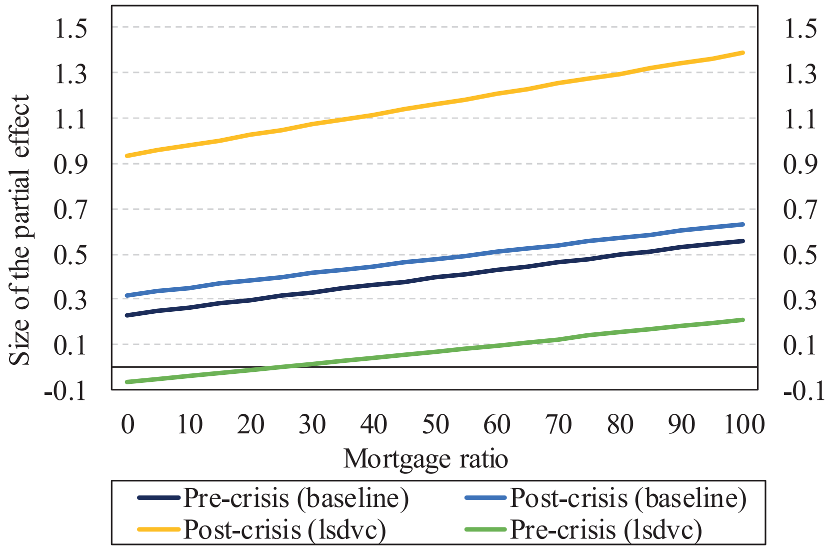
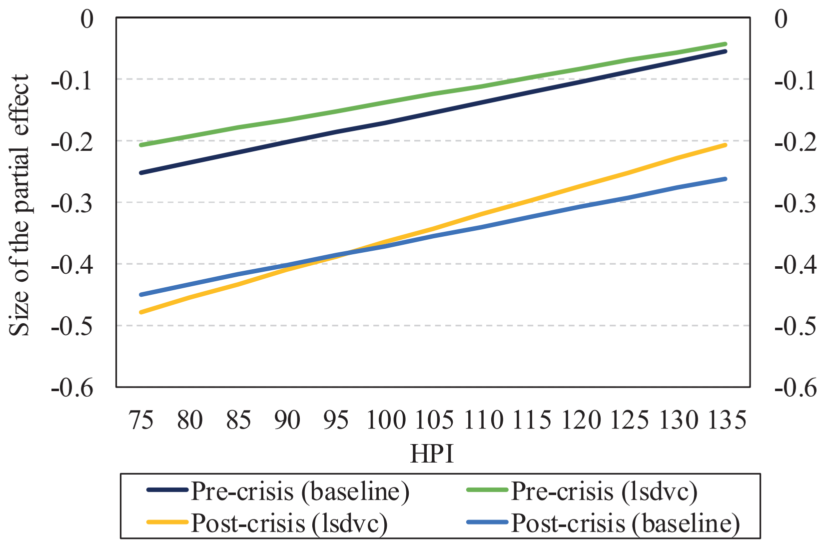



*Figure 4: Partial effect of mortgage loan exposure on bank risk (before and after the crisis)*



## 5. Robustness tests

As our results are potentially influenced by several decisions on estimates, we carried out a number of robustness tests. (1) We examined whether our statements hold when we control for other macro variables which probably influence the performance of mortgage loans. (2) The selection of the risk indicator may be of key importance, since the way in which a bank's level of risk is measured is not obvious. For that reason, we also performed estimates with the Z-risk indicator, which is frequently used in the literature as a proxy variable for bank risk and we also tested a modified version of our own composite risk indicator. (3) Static models estimated by earlier studies were also run. (4) Dummy variables for the share of mortgage loans, and for the (5) House Price Index – both appearing in the interaction term – were generated with other limits. (6) Finally, we examined whether using other estimation methods or excluding bank control variables had a meaningful effect on our conclusions.

Mortgage lending influences the level of bank risks both through housing market developments and, for example, through other macroeconomic variables that influence households' financial situation. In our previous estimates, we used time fixed effects to control for the macro environment; however, in our opinion it is also worthwhile to consider certain macro variables directly to confirm our estimation results. Apparently, when the model includes households' disposable income, the GDP or the short-term interest rate, there are no major changes to either the significance or the extent of the effect produced by house prices. Importantly, the introduction of quarterly lags for these macro variables does not influence the effect of house prices in terms of either size or direction (*Table 6* in the Annex).

As a robustness test, we used an alternative indicator to measure developments in the housing market. We examined the effect of the house price gap, i.e. focusing specifically on overheating (*Table 6* in the Annex). In this manner, we can show in an explicit way that the *deviation hypothesis* was stronger for Hungary in the sample period, as the house price gap precisely measures the deviation of house prices from their fundamental value. Using the house price gap, the same result is obtained as with the estimation based on the real price index, i.e. a larger house price gap leads to higher bank risk, and the effect is stronger in the case of higher mortgage loan ratio (*Figure 7* shows that the partial effect is positive and the increasing function of mortgage loan ratio), which confirms our previous findings. Moreover, the estimated partial effect of the mortgage loan ratio is positive in an overheated environment (i.e. larger than 5 per cent gap), i.e. more active mortgage lending suggests higher bank risk. However, if house prices are below their fundamental value, the partial effect of mortgage lending is just the opposite, as there is a negative relationship between mortgage loan ratio and bank risk (*Figure 8* in the Annex).

The literature pays little attention to the extent to which the method of measuring the level of bank risk determines the results obtained. Our chosen risk indicator tries to provide a complex understanding of the level of risk at a credit institution, as it contains information on the solvency position, portfolio quality, profitability, and the liquidity position as well. We examined whether our results would change if we use equal weights to construct our composite risk indicator (instead of the weights shown in *Table 1*). Our results proved to be very robust to this change (*Table 7* in the Annex). The Z-risk indicator – which is used by other studies – primarily captures the solvency situation of a bank, i.e. it is considerably more restricted than the indicator used in our study. We examined the results obtained when using the Z-risk indicator as a dependent variable (*Table 7* in the Annex). As a higher value of Z-risk equates to higher stability (in contrast to our composite risk indicator), both the *deviation hypothesis* and the inference that higher mortgage leads to higher risk, also holds when bank risk is measured by the Z-risk indicator, although the estimated effect is weakly significant.

We estimated a dynamic panel regression as our basic estimation since – from a theoretical point of view – we think that the riskiness of an individual bank is persistent. As a robustness check, we also ran a static estimation, on the one hand for a technical reason, i.e. based on the construction our dependent variable is not fully continuous, and on the other hand for the sake of comparison, as previous studies used static models. In the baseline specification which regresses our composite bank risk indicator, the static and dynamic models lead to the same inferences, with smaller, but strongly significant coefficients in the case of the dynamic specifications (as the lagged dependent variable has significant explanatory power in these). By contrast, when the Z-risk indicator is modelled, there is a large difference in the size and significance of the results of the static and dynamic specifications (*Table 7* in the Annex). The coefficient of the lagged dependent variable is very large (0.9) in case of the Z-risk, indicating strong persistence. According to these results, including the lagged dependent variable may be particularly recommended in the case of the Z-risk indicator, since ignoring the persistence of bank risk can lead to incorrect inferences.

One of our initial models included a dummy variable to capture a bank's relative mortgage lending activity. As a robustness test, we ran several estimations with dummy variables generated by other thresholds. Similarly, we estimated models in which the threshold, used to create dummy variables for the examination whether the partial effect of the mortgage ratio differs in case of various house price environment, was altered. *Table 8, Table 9* and *Figure 9* in the Annex show that our models are robust to the above-mentioned modifications.

We estimated our baseline model using different methods (*Table 10*). *Figure 10* and *Figure 11* in the Appendix show that all of the tested estimation methods lead to the same conclusions: (i) higher real house prices are accompanied by higher bank risk and this effect is stronger for banks with a higher mortgage loan ratio; (ii) a higher mortgage loan ratio basically lead to lower risk, but increasing the share of mortgage loans when house prices are relatively high (suggesting a potentially overheated housing market) tends to raise bank risk. These conclusions also hold when we exclude bank control variables as an alternative specification (see the last column in *Table 10*).

## 6. Conclusion

House prices may have a significant impact on bank operations in several respects. Changes in real estate prices may affect the level of risk in financial institutions through both household mortgage lending and corporate project lending. The literature has no clear conclusion on this impact mechanism. Based on the *collateral value hypothesis*, we would expect rising house prices to mitigate risk, whereas based on the *deviation hypothesis* a strong rise in house prices would rather intensify risk, especially if the house price level is far from its fundamental value. Koetter and Poghosyan (2010) underline the importance of examining each country individually due to the different directions, since the dominant effect may vary by country.

In our paper, we examined the relationship between house prices and bank risks. Our results confirmed the *deviation hypothesis* for Hungary between 2000 and 2016, i.e. rising house prices led to an increase in the level of bank risk. The *deviation hypothesis* is also confirmed by the estimates in which the house price gap, a direct measure of housing market imbalances was included. Moreover, the size of the partial effect of house prices on bank risk depends on banks' exposures: for banks that are more active in mortgage lending, a housing market boom can drive more risks.

Based on our estimations, timing of the effect of house prices is influenced by banks' activity in mortgage lending. In the case of banks focusing on mortgage lending, changes in house prices have a quick and strong effect on bank risk that diminishes over time, whereas in the case of banks with smaller mortgage loan portfolios, the effect of driving risk is slower.

According to the estimates run on subsamples for the periods preceding and following the onset of the crisis, in both periods there may be an obvious positive relationship between house prices and bank risk, which may be stronger for banks characterised by higher activity in mortgage lending. This suggests the dominance of the deviation effect in Hungary both before and after the onset of the crisis, i.e. rising house prices may lead to increasing bank risk.

Compared to previous studies, in our analysis we paid considerably more attention to the potentially divergent effects of certain estimation factors. We found that our findings, both the *deviation hypothesis* and the inference that higher mortgage exposure leads to higher risk, are robust in terms of both (i) estimation method and (ii) model specification.

The fact that the *deviation hypothesis* is confirmed suggests that both banks and households tend to undertake excessive risks during a housing market boom, which is important for macroprudential policy. Moreover, our estimation result suggests that higher mortgage loan ratios mitigate bank risk only to a certain point, and thus in the case of an overheated housing market, increasing the share of the mortgage loan portfolio can lead to higher bank risk, which does not necessarily appear in risk parameters, since for example increasing house prices lead to smaller LGD. This underlines the importance of closely monitoring mortgage lending and may suggest the use of macroprudential tools such as SRB (Systemic Risk Buffer) for this risky segment.

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## Appendix

*Table 5: Descriptive statistics*

| | Mean | Standard deviation | Minimum | 25% percentile | Median | 75% percentile | Maximum |
|---|---|---|---|---|---|---|---|
| EBA-risk | 37.0 | 12.0 | 8.2 | 28.4 | 35.9 | 44.4 | 84.0 |
| Mortgage Ratio | 30.4 | 23.8 | 0.1 | 8.6 | 28.9 | 45.7 | 99.4 |
| House Price Index (HPI) | 112.3 | 16.8 | 84.7 | 98.4 | 111.0 | 130.0 | 135.9 |
| Mortgage Ratio * HPI | 3380.1 | 2742.7 | 8.4 | 1035.9 | 3029.3 | 4860.9 | 13053.0 |
| CAR | 14.3 | 8.7 | 2.1 | 9.9 | 12.1 | 15.6 | 133.3 |
| NPL | 8.9 | 8.0 | 0.0 | 2.4 | 6.0 | 14.4 | 32.2 |
| ROA | 1.4 | 3.3 | -20.2 | 0.1 | 1.2 | 2.2 | 19.5 |
| Liquid assets ratio | 18.6 | 10.8 | 0.4 | 10.6 | 17.3 | 25.1 | 69.8 |
| Foreign funds ratio | 28.3 | 17.3 | 0.0 | 13.4 | 26.9 | 41.1 | 76.5 |
| Real Disposable Income (agr) | 1.5 | 3.2 | -6.8 | -0.8 | 2.0 | 3.8 | 8.5 |
| Real GDP (agr) | 2.1 | 2.9 | -7.5 | 1.2 | 3.1 | 4.2 | 5.0 |
| Interest Rate (agr) | -9.7 | 28.9 | -47.9 | -35.6 | -13.0 | 12.9 | 94.2 |
| Z-risk | 1.6 | 2.1 | -3.9 | 0.3 | 1.0 | 2.5 | 11.3 |

Note: The abbreviation "agr" refers to annual growth rate. Disposable Income and GDP are in real terms. The Interest Rate in the model is the Hungarian 3-month interbank interest rate.

*Figure 5: Quarterly real house price index (HPI) of Hungary (2001 Q1 = 100%)*

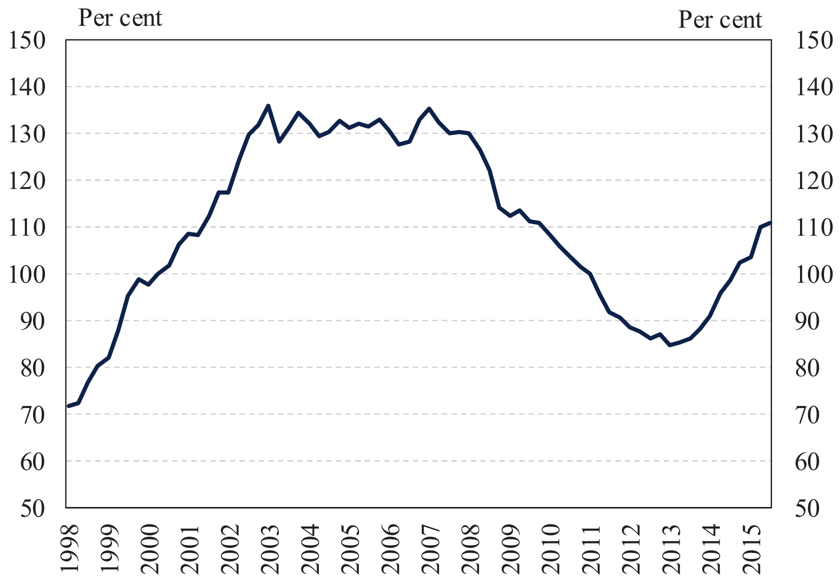



*Figure 6: Box plot of the banking sector's mortgage loan ratio*

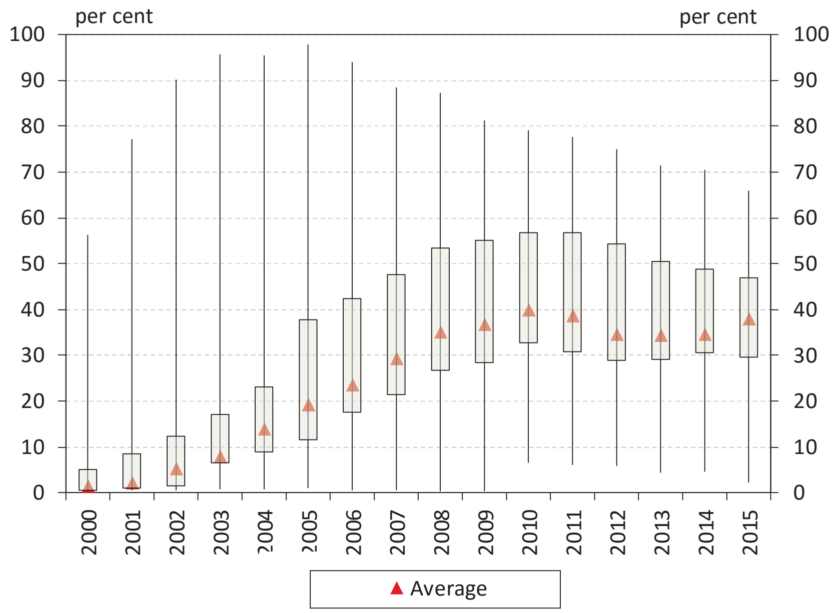


*Table 6: Estimation results with various macro variables and alternative house price variable*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Lagged Bank Risk | 0.367*** | 0.367*** | 0.367*** | 0.367*** | 0.392*** |
| | (0.0424) | (0.0425) | (0.0425) | (0.0425) | (0.0422) |
| House Price Index (HPI) | 0.217*** | 0.209*** | 0.237*** | 0.188*** | |
| | (0.0220) | (0.0229) | (0.0251) | (0.0227) | |
| Mortgage Ratio | -0.396*** | -0.396*** | -0.396*** | -0.396*** | -0.0203 |
| | (0.0756) | (0.0757) | (0.0757) | (0.0757) | (0.0316) |
| Mortgage Ratio * HPI | 0.00315*** | 0.00315*** | 0.00315*** | 0.00315*** | |
| | (0.000611) | (0.000612) | (0.000612) | (0.000612) | |
| GDP (agr) | | -0.00770 | | | |
| | | (0.0691) | | | |
| Disp. Income (agr) | | | -0.463*** | | |
| | | | (0.0880) | | |
| Interest Rate (agr) | | | | 0.0270*** | |
| | | | | (0.00305) | |
| House Price Gap (HPG) | | | | | -0.0186 |
| | | | | | (0.0630) |
| Mortgage Ratio * HPG | | | | | 0.00378** |
| | | | | | (0.00151) |
| Bank controls | YES | YES | YES | YES | YES |
| Bank fixed effects | YES | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES | YES |
| Observations | 843 | 843 | 843 | 843 | 843 |
| Groups | 13 | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.614 | 0.614 | 0.614 | 0.614 | 0.607 |

Note: The abbreviation “agr” refers to annual growth rate. Disposable Income and GDP are in real terms. The Interest Rate in the model is the Hungarian 3-month interbank interest rate. Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

*Figure 7: Partial effect of the House Price Gap on bank risk*

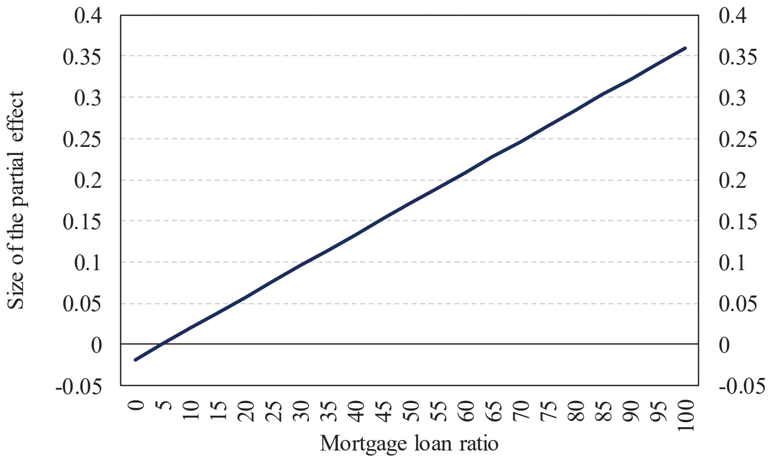



*Figure 8: Partial effect of the mortgage loan ratio on bank risk for the model including the House Price Gap*

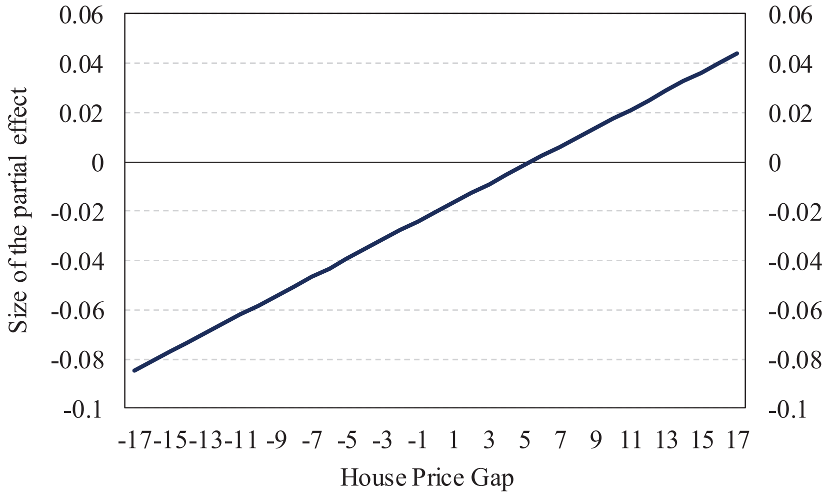


*Table 7: Estimation results with different risk measures*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dynamic | | | Static | | |
| Lagged EBA-risk | 0.367***<br>(0.0424) | | | | | |
| House Price Index (HPI) | 0.217***<br>(0.0220) | 0.258***<br>(0.0283) | -0.000395<br>(0.000950) | 0.320***<br>(0.0195) | 0.420***<br>(0.0211) | 0.0164***<br>(0.00268) |
| Mortgage Ratio | -0.396***<br>(0.0756) | -0.343***<br>(0.0817) | 0.00533<br>(0.00331) | -0.614***<br>(0.0923) | -0.567***<br>(0.113) | 0.135***<br>(0.0144) |
| Mortgage Ratio * HPI | 0.00315***<br>(0.000611) | 0.00199***<br>(0.000646) | -4.85e-05*<br>(2.86e-05) | 0.00499***<br>(0.000784) | 0.00345***<br>(0.000973) | -<br>0.00131***<br>(0.000136) |
| Lagged EBA-risk (E) | | 0.420***<br>(0.0460) | | | | |
| Lagged Z-risk | | | 0.909***<br>(0.0221) | | | |
| Bank controls | YES | YES | YES | YES | YES | YES |
| Bank FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Observations | 843 | 843 | 842 | 843 | 843 | 843 |
| Groups | 13 | 13 | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.614 | 0.637 | 0.975 | 0.546 | 0.547 | 0.482 |

Note: (E) indicates: equal weights. Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

*Table 8: Estimation results of models with various mortgage exposure limits*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lagged Bank Risk | 0.351*** | 0.386*** | 0.388*** | 0.383*** |
| | (0.0443) | (0.0416) | (0.0415) | (0.0411) |
| House Price Index (HPI) | 0.226*** | 0.212*** | 0.211*** | 0.216*** |
| | (0.0213) | (0.0208) | (0.0203) | (0.0208) |
| Mortgage Ratio >25% | -20.71*** | | | |
| | (4.126) | | | |
| Mortgage Ratio >25% * HPI | 0.178*** | | | |
| | (0.0370) | | | |
| Mortgage Ratio >30% | | -12.74*** | | |
| | | (3.241) | | |
| Mortgage Ratio >30% * HPI | | 0.104*** | | |
| | | (0.0298) | | |
| Mortgage Ratio >35% | | | -10.07*** | |
| | | | (3.182) | |
| Mortgage Ratio >35% * HPI | | | 0.0956*** | |
| | | | (0.0312) | |
| Mortgage Ratio >40% | | | | -10.86*** |
| | | | | (2.894) |
| Mortgage Ratio >40% * HPI | | | | 0.100*** |
| | | | | (0.0258) |
| Bank controls | YES | YES | YES | YES |
| Bank fixed effects | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES |
| Number of observations | 843 | 843 | 843 | 843 |
| Number of groups | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.617 | 0.610 | 0.609 | 0.609 |

Note: Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

*Table 9: Estimation results for various House Price Index limits*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lagged Bank Risk | 0.384*** | 0.377*** | 0.383*** | 0.389*** |
| | (0.0413) | (0.0420) | (0.0412) | (0.0419) |
| Mortgage Ratio | -0.0879** | -0.0724** | -0.0540 | -0.0317 |
| | (0.0335) | (0.0351) | (0.0398) | (0.0369) |
| House Price Index (HPI) | 0.218*** | 0.218*** | 0.218*** | 0.215*** |
| | (0.0227) | (0.0224) | (0.0226) | (0.0236) |
| Mortgage Ratio * HPI>100 | 0.0844*** | | | |
| | (0.0268) | | | |
| Mortgage Ratio * HPI>110 | | 0.0834*** | | |
| | | (0.0265) | | |
| Mortgage Ratio * HPI>120 | | | 0.0700** | |
| | | | (0.0292) | |
| Mortgage Ratio * HPI>130 | | | | 0.0481* |
| | | | | (0.0265) |
| Bank controls | YES | YES | YES | YES |
| Bank fixed effects | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES |
| Number of observations | 843 | 843 | 843 | 843 |
| Number of groups | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.608 | 0.610 | 0.608 | 0.605 |

Note: Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

*Figure 9: Partial effect of the mortgage loan ratio on bank risk for various House Price Index limits*

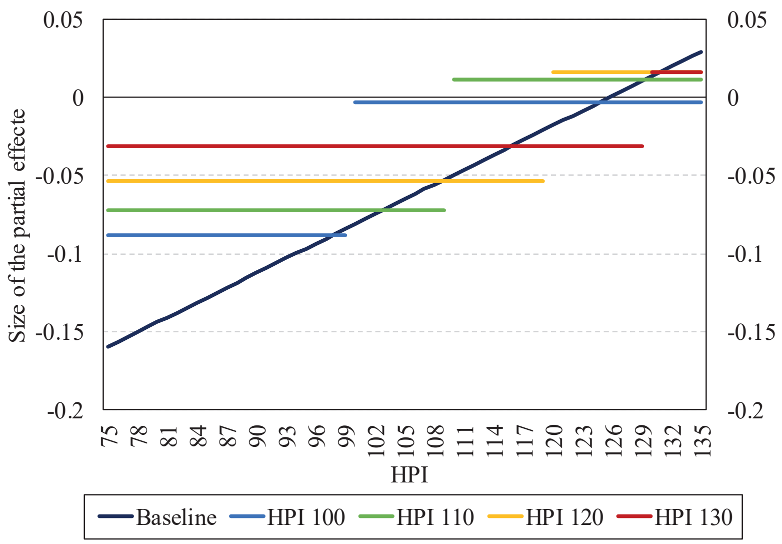


*Table 10: Results obtained by different estimation methods*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Estimator: | Within | LSDV | Within | LSDV | LSDVC | Within |
| St. Error: | DK | DK | Robust | Robust | Bootstrap | DK |
| Lagged Bank Risk | 0.367*** | 0.367*** | 0.367*** | 0.367*** | 0.391*** | 0.578*** |
| | (0.0424) | (0.0428) | (0.0570) | (0.0400) | (0.0337) | (0.0341) |
| Mortgage Ratio | -0.396*** | -0.396*** | -0.396*** | -0.396*** | -0.391*** | -0.146** |
| | (0.0756) | (0.0762) | (0.0948) | (0.0862) | (0.116) | (0.0702) |
| House Price Index (HPI) | 0.217*** | 0.192*** | 0.0565 | 0.0565 | -0.140 | 0.119*** |
| | (0.0220) | (0.0211) | (0.0596) | (0.0499) | (0.538) | (0.00988) |
| Mortgage Ratio * HPI | 0.00315*** | 0.00315*** | 0.00315*** | 0.00315*** | 0.00308*** | 0.00183*** |
| | (0.000611) | (0.000616) | (0.000684) | (0.000704) | (0.000908) | (0.000470) |
| Bank controls | YES | YES | YES | YES | YES | NO |
| Bank FE | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES |
| Observations | 843 | 843 | 843 | 843 | 843 | 843 |
| Groups | 13 | 13 | 13 | 13 | 13 | 13 |
| R-squared (within) | 0.614 | - | 0.614 | - | - | 0.534 |
| R-squared | - | 0.7821 | - | 0.758 | - | - |

Note: DK indicates: Driscoll-Kraay. Regressions also include the following bank-level controls: capital adequacy ratio, the ratio of liquid assets to total assets, the ratio of non-performing loans, the return on total assets, the share of foreign funds within the balance sheet. The corresponding standard errors are computed using the Driscoll–Kraay method. *** significant at 1%, ** significant at 5%, * significant at 10%.

*Figure 10: Partial effect of house prices on bank risk in models estimated by different methods*

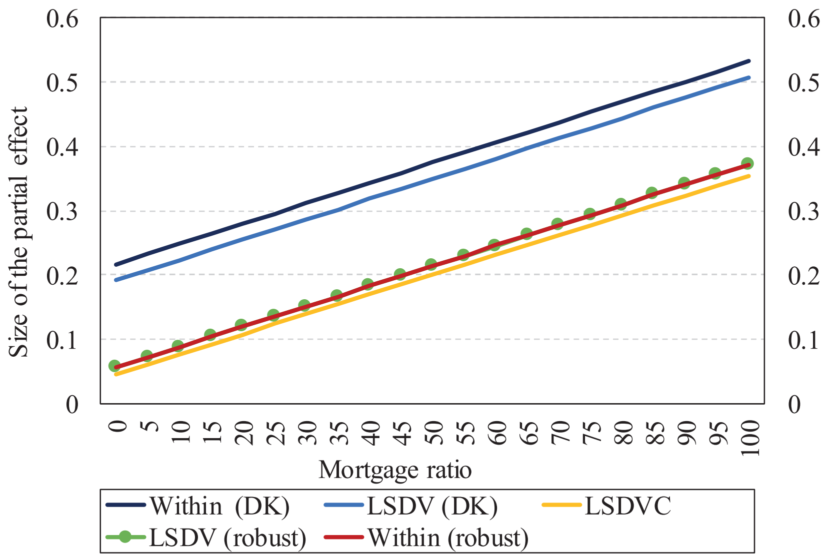
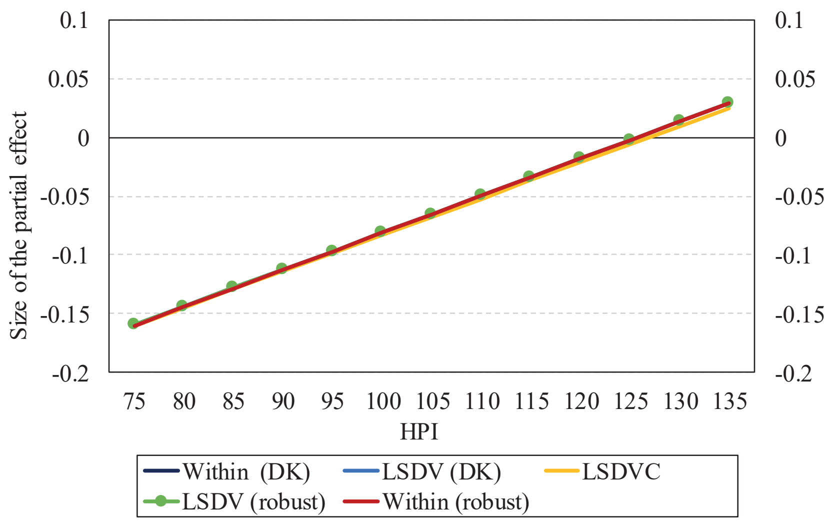



*Figure 11: Partial effect of the mortgage loan ratio on bank risk in models estimated by different methods*



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