“The impact of mandatory amortization of mortgage loans on the housing market “

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Abstract: Using transactions data on apartment sales in Sweden, and taking in consideration the decision made by Swedish Finansinspektion, we examined the effect of mandatory mortgage amortization on apartment auction prices/bidding premiums. Our results showed that there was effect of the mandatory amortization rule as macroprudential measure on the bidding premium and housing prices (starting and final auction prices). We found negative CAARs after the day of the adoption of the measure. To the extent that house prices reflect rational expectations of future changes in fundamentals, this negative price response could imply negative prospects in the underlying housing market as perceived by market agents. Negative CAARs were confirmed by both hedonic and spatial models. Far lower AIC statistics prove that spatial models are better modeling the price/premium dynamics and can compensate for the omitted variables.

Keywords: housing market, event study, propensity score, hedonic model, panel, spatial model

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Introduction

Current hot topic is the housing market and continuous increase of prices of house prices. All-important stakeholders are monitoring its dynamics, try to predict its price level, to locate its drivers and asses the effects on the economy from its future price direction.

House prices have risen to high levels, slowing only recently. Research suggests that house prices are 12 percent above long-run equilibrium (IMF Working Paper 15/276). Main reasons for this trend is increased population and slow response of the housing supply to the increase in demand, due to the restrictions on land acquisition and planning procedures at the municipal level (IMF Country Report No. 16/355). As pointed out in this report, house price gains provide incentives for households not to amortize loans and take out even larger loans relative to income, aided by longer loan maturities mortgage interest rate deductibility and the lack of a property tax, further propel house demand.

Household debt has been rising relative to income with new borrowers taking on increasingly high debts, which boosts macro-financial risks. A rising share of new mortgage debtors in Sweden take out mortgages that exceed 50 % of the value of the home (ECB opinion, 2016). In addition, a large percentage of loans in Sweden are not amortized at all but prolonged at maturity. Moreover, some households have unduly optimistic expectations of future housing prices and interest rate levels. Data shows that overall household indebtedness is high in relation to disposable income.

Eventual quick reversal of the prices could have high macroeconomic impact and could hurt banking system, as the biggest collateral holder of real estate. Indirectly, as the banks will probably respond with restricted credit offer, decline in the prices finally could slow solid economic growth of the Swedish economy.

Financial institutions try to slow down growth of house prices and increased household debt. Finansinspektionen (the Swedish financial supervisory authority) adopted several macroprudential measures to normalize its dynamics, while trying not to provoke counter-effects in the other segments of the financial system (Appendix 1). Focus of these measures is credit supply. Having many weapons in the macroeconomic arsenal, Financial Inspection targeted one of the characteristics of the Swedish banking system and adopt mandatory mortgage amortization rule.

Swedish banking system is specific in that mortgages provided to the physical persons before June 2016 does not have mandatory amortization and require from the creditor to pay only the interest, not the principal. Data for 2014, gathered by Finansinspektionen records that only 60 % of households made principal payments on their mortgages. In comparison, in other countries, loans with no amortization requirements are considered high-risk, and are subject to more restrictive lending standards. This type of contract, which is enabling creditors to keep high persistent debt are making the creditors vulnerable to shocks, such as unexpected changes in income, housing prices or interest rates. Especially highly leveraged households are found to be sensitive to economic shocks. Finansinspektionen considers that the main risks lie with households whose mortgages exceed 50 % of the value of the property securing the mortgage. This type of households could be one of the crises triggers even in the event of small shocks.

The new mandatory mortgage amortization rule provides that all new loans granted for housing purposes on or after 1 June 2016 and secured by a property must include provisions on amortization requirements if the mortgage exceeds 50 % of the property's market value (ECB opinion, 2016). The rule also provides that the amortization requirements apply to existing loans if the existing loan amount is increased. The amortization amount is calculated on the basis of total indebtedness (i.e. existing indebtedness together with the increased loan amount). As risks increase with higher household indebtedness, the draft proposal adopts a progressive amortization requirement according to which new mortgages exceeding 70 % of the property's market value must be amortized by at least 2 % per year of the total loan amount, and by at least 1 % per year of the total loan amount when the new mortgage amounts to more than 50 but less than 70 % of the property's market value. In order to avoid the regulation increasing cyclical fluctuations, the draft proposal provides that as a general rule the market value of a property should not be reassessed more than once every five years. The rule includes an option for lenders not to apply the amortization requirements in relation to loans granted to finance the acquisition of newly constructed homes. A borrower acquiring a newly constructed home would be exempt from the mortgage amortization requirements.

Although authorities have undertaken measures to increased house price levels and household debt, they are preparing some new macroprudential measures (cap on debt-to-income ratio - DTI).

Therefore, it is of great importance to see the direct impact of this measures, especially on the house price dynamics, so that authorities do not constrain the credit supply and demand in excess of the optimal level. The direct effect of these measures on the house price dynamics are not easy observable, since the housing market has other drivers and has quite diverse main market product (apartments), transacted by varied owners with different housing / investment needs and expectations with different horizons.

This paper examined the effect of the measure on the price level, using several variables: starting price of the apartments per square meter, bidding premium and final price per square meter. Similar to financial markets practice, we use CAAR (Cumulative average abnormal return) methodology for assessing the impact of event (adopting mandatory amortization rule) on the prices. In this CAAR framework, the implementation of mandatory amortization rule we treat as an 'event' and we assess whether 'abnormal returns' can be identified following its adoption.

If mandatory amortization influences the credit repayment capability of current and potential home owners and foster banks to apply stricter credit approval conditions, mortgage credits would be less available and more expensive. Decreased credit supply should lower house demand and housing prices should decrease in response, leading to an negative 'abnormal return' on housing market prices, following the introduction of this measure.

Our results showed negative CAARs after the day of the adoption of the measure, which confirm that adoption of the mandatory amortization as macroprudential measure was successful. To the extent that house prices reflect rational expectations of future changes in fundamentals, this negative price response could imply negative prospects in the underlying housing market as perceived by market agents.

Literature Background

Investigating the effectiveness of the macroprudential policy measures on stabilizing house prices and housing credit, undertaken by monetary (financial authority), attracts impressive attention from the researchers and hence, the literature on this field is rapidly expanding.

Also, growing body of research has documented the use of tools other than the short-term interest rate in various countries and examined their effectiveness in damping house prices through dumped credit growth. Borio and Shim (2007) documented macroprudential and monetary policy measures taken by 18 economies with the aim of influencing credit and housing prices. Using an event study methodology, they found that macroprudential measures reduced credit growth by 4 to 6 percentage points in the years immediately following their introduction, while house prices slowed in real terms by 3 to 5 percentage points. It should be noted that Borio (2011) is using macro data using data from several countries, while our paper uses micro data and data about Sweden when performing event study.

Kuttner and Shim, (2013) in their paper investigates the effectiveness of nine non-interest rate policy tools, including macroprudential measures, in stabilizing house prices and housing credit. Using conventional panel regressions, they found that housing credit growth is significantly affected by changes in the maximum debt-service-to-income (DSTI) ratio, the maximum loan-to-value ratio, limits on exposure to the housing sector and housing-related taxes. But, when they were using the mean group and panel event study methods they found that only the DSTI ratio limit has a significant effect on housing credit growth. Oppositely, our paper compared to the policies considered, is focusing on mandatory amortization rule as the policy tool with a impact on house price appreciation.

Hull (2015) evaluate mortgage amortization requirements as a tool for reducing household indebtedness and income shock vulnerability in the long run. He finds that intensifying the rate and duration of amortization is largely ineffective at reducing indebtedness in a realistically-calibrated model. In the absence of implausibly large refinancing costs or tight restrictions on the maximum debt-service-to-income ratio, the policy impact is small in aggregate, over the lifecycle, and across employment statuses. It should note that his work in the form of simulation exercise is done before the mandatory amortization rule is adopted. In our paper we work with real transactions data, covering the period before and after the rule adoption date, for which we find the event methodology as most appropriate in this context.

Event methodology that we use is similar to one already used in finance to assess the impact of event surprises on stock prices. Cornerstone in the field of finance is the work of Fama, Fisher, Jensen, and Roll (1969), in which they involve calculating cumulative average abnormal returns (“CAARs”). In our case of the housing market, instead of CAPM as the equilibrium asset pricing model, we use hedonic price model for estimating house prices. In the later phase we also use spatial model for estimating house prices.

It would be naive if we directly compare the averages, medians or cumulative abnormal returns between this two samples due to selection bias which will influence treatment effects (Angrist, Pischke, 2005). Nanda and Ross (2009) used propensity score techniques from the treatment effects literature with a traditional event study approach to examine whether the adoption of seller disclosure laws has reduced the magnitude of the asymmetric information problem in residential property markets. Propensity score is just one of the semi-parametric and non-parametric matching methods, which helps to improve parametric statistical models and reducing model dependence by preprocessing data (Ho, Imai, King, and Stuart, 2007). Similarly, we use combination of these two techniques (event study and propensity score), except for we compare the actual median returns (premiums) and predicted median returns (premiums) from the hedonic and spatial models fitted on daily transaction data, while Nanda and Ross (2009) are using a quarterly panel of housing price indices.

Hedonic model explains the house price using its characteristics. First paper that used this model is the “new theory of consumer demand” presented by Lancaster in 1966, Later on this model was further developed by Rosen in 1974. Estimation of the value of particular attributes indirectly carries information about the outcome of supply and demand changes (Rosen, 1974). Since hedonic models represent industry standard in estimating housing prices, we have no doubt to use them to get predicted prices, which we later compare with real prices, om order to get abnormal returns.

Spatial dependence of characteristics and values coupled with incomplete information make spatial dependence of the regression residuals almost inevitable. Ignoring this phenomenon represents one of the most common geographic errors (Thrall, 1998). Rather than eliminating the problem of spatial residual dependencies through models using complicated functions of many variables, spatial statistical methods typically keep simple models of the variables and augment this with simple models of the spatial error dependence. Alternatively, spatial techniques may use spatial lags of the dependent and independent variables to reduce spatial error dependence (Dubin, Pace & Thibodeau, 1999). In the recent literature, hedonic models are combined with spatial techniques in order to improve estimation and prediction of house prices.

Our contribution in this field of research is that we combine several techniques (event study, propensity matching and spatial analysis) in order to assess the impact of macro prudential measures on housing prices.

Methodology

To understand the impact of mandatory amortization on housing prices, we perform an event study. We try to examine if the housing prices after some event display abnormal returns (i.e. returns in excess of their expected return). We are studying a population of transaction prices and bidding premiums, where some sellers/buyers sells/buy before or after the event date (date of adoption of mandatory amortization rule). We consider the transactions before the event date as control group, while the others as treated group.

Firstly, we used panel data as parametric method to estimate the effect of the mandatory amortization rule. For that purpose, we aggregate the transaction data to monthly data using median on the variables: bidding premium, returns on starting price per m2 and returns on final price per m2.

Our model uses index i for municipality, t for month. The terms α_i and γ_t capture the municipality fixed effect and the monthly fixed effect, respectively. The dependent variable is either bidding premium (in Eq.1) or the log change in the housing prices Y_{it} (in Eq.2); $X_{it}$is a vector of the characteristics of the apartment; and D_t is a binary variable that is one, if the measure has been adopted immediately preceding period t so that$(D_t - D_{t-s})$ takes on a value of 1 for s months (our event window) immediately following the adoption of the law.

$$p_{it} = \alpha_i + \gamma_t + \beta * X_{it} + \delta * (D_t - D_{t-s}) + \varepsilon_{it} \quad (1)$$

$$\log(Y_{it}) - \log(Y_{it-1}) = y_{it} = \alpha_i + \gamma_t + \beta * X_{it} + \delta * (D_t - D_{t-s}) + \varepsilon_{it} \quad (2)$$

Further, we test CAAR methodology for assessing the impact of event (adopting mandatory amortization rule) on the prices. The algorithm for calculating the CAARs is:

1. Fit the model for the period before the event, using log of the transaction prices and use the fitted model on the data for the period after the event to predict the prices in this period,
2. Calculate the median daily prices, using predicted prices and realized prices from each transaction. This helps eliminate idiosyncrasies in measurement due to particular stocks.
3. Knowing daily predicted and realized prices, calculate daily returns on predicted and realized prices,
4. Calculate daily abnormal returns (“ARs”) for the period after the event, as the difference between daily returns on predicted and daily returns on realized prices,
5. Sum the average abnormal returns over the T days in the event window (i.e. over all times t) to form the cumulative average abnormal return (CAAR).

We test several event dates, including the day of announcement of intended measure and the day of the adoption of measure. We define the estimation window from the first day to the days: (-120, -90, -60, -30 respectively,) relative to the event day. Implicitly we assume that, for example, returns more than 30 days prior to the event are not influenced by the event itself.

Then, we are combining the event methodology with the propensity score matching, as it can help to reduce the bias from non-linear selection on observables. In this way the comparison of average impact is performed using similar treated / control observations, homogeneous in the terms of the likelihood of experiencing treatment (selling/buying after the adoption of the measure). The observations on rental transactions are assigned to treatment and control groups, based on a highly nonlinear relationship between observable controls and the transacting with reference to event date. We consider only a single dichotomous causal (or treatment) variable, which takes a value of 0, if the transaction is before the event date (it is untreated and serve as control) and 1, if the transaction is after the event date (receives the treatment). In the process of data matching, the observations are selected, duplicated, or selectively dropped from our data, and it is done without inducing bias. The propensity score–defined as the probability of receiving the treatment given the covariates–is a key tool. There are many methods that offer this preprocessing: exact, sub-classification, nearest neighbor, optimal, and genetic matching. In our analysis we use nearest neighbor matching.

When modeling the data, we start from the simplest ordinary form of the hedonic model to estimate the price in period t of a dwelling h with a transaction price p_h as follows:

$$y_h = \alpha + Z\beta + \varepsilon_h \quad (3)$$

where, y_h is an $H \times 1$ vector with elements $y_h = \ln p_h$,, Z is an $H \times C$ matrix of characteristics, (some of which may be dummy variables), β is a $C \times 1$ vector of characteristic shadow prices.

In order to take in consider effect of the time, we include time as the trend:

$$y_h = \alpha + Z\beta + \tau t + \varepsilon_i \quad (4)$$

where, τ is scalar of daily log-price change and t *is* $T \times 1$ vector with time periods. Finally, H, C and T denote respectively the number of dwelling, characteristics and time periods in the data set.

To take in consider the effect of location and time, we include the municipal codes and time trend:

$$y_h = \alpha + Z\beta + B\gamma + \tau t + \varepsilon_i \quad (5)$$

where the additional term B is an $H \times (M\text{-}1)$ matrix of dummy variables, γ is an $(M\text{-}1) \times 1$ vector of parameters, and M is the number of municipality identifiers.

Finally, we use spatial Spatial autoregressive model (SAR) in predicting prices, as in LeSage and Pace (2009), adding time trend as well:

$$y_h = \alpha + Z\beta + \rho W y_h + \tau t + \varepsilon_i \quad (6)$$

where W is spatial weights matrix and ρ is a scalar that measures the average locational influence of the neighbouring observations on each observations.

Data

For the purposes of this research, we used data on concluded sales of apartments through public bidding from the area of Skane.

The data cover the period of almost 2.5 calendar years on daily basis from 2015-02-01 to 2017-07-28. Starting number of transactions is 8204 transactions, but after cleaning the outliers we work with sample of around 8186 transactions. When we further pre-process data, we were modeling using the sample between 2,500 and 3,200 transactions of matched data (by propensity score).

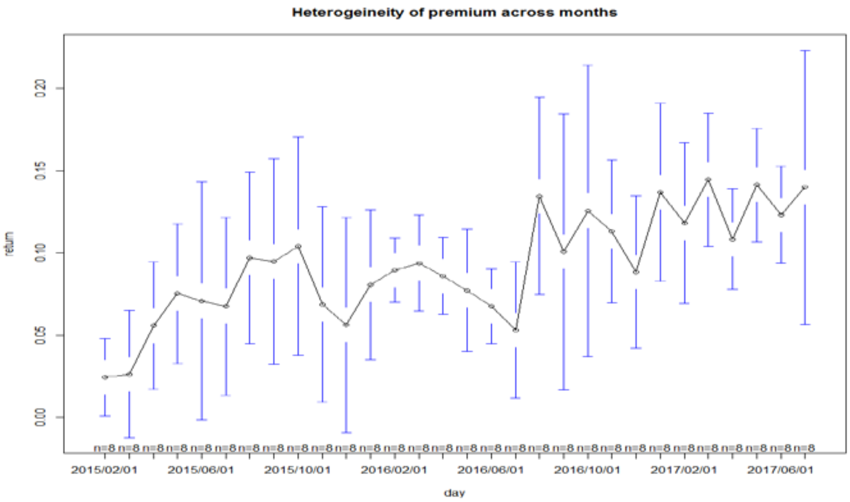
The data on particular transaction includes: municipality, address, date of transaction, latitude, longitude, floor in the building, year of building, number of rooms, size of the apartment, start price per m2, bidding premium (in percentage) and final sold price per m2.

For the purpose of parametric panel data analysis, data was structured as a panel, where we aggregated the transaction data to monthly data using median on the variables: bidding premium, returns on starting price per m2 and returns on final price per m2s. finaly, we work with 203 x 8 wide panel, which includes municipality, month, dependent variable (premium or price) and 5 independent variables.

Data analysis

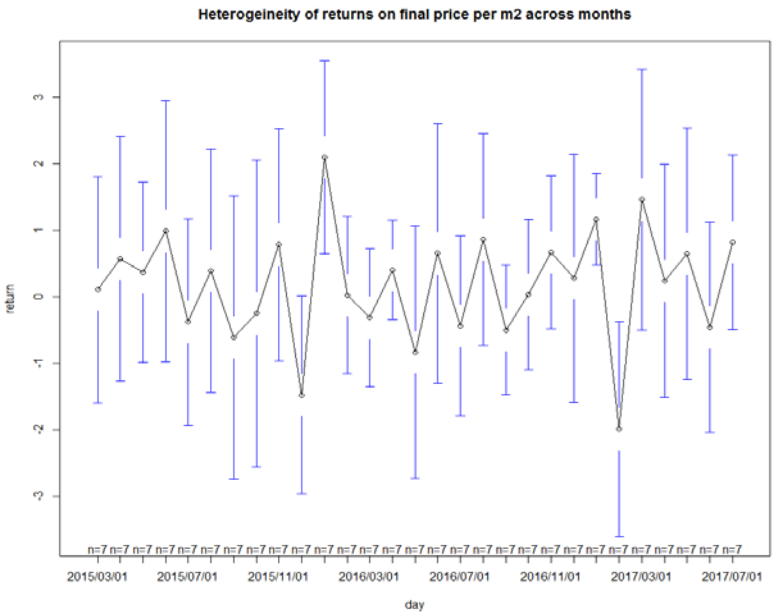
Panel data results on the bidding premium show that the measure has only temporarily decrease of the median level of premium. In the period before the rule was adopted, the premium has fallen from 10% to around 5%, and after a while jumped to the new level of around 12%.
This temporary correction was probably due the process of adjusting the market expectations. One possible explanation would be that before the decision, the buyers might be cautious about the effects of the measure and maybe they postpone the decision to buy, but once they realize that offered starting prices are not changed downwards, they re-adapt their expectations. Therefore, dummy variable coefficient δ is positive and significant, opposite to the expected effects from the measure.

Figure 1.



Panel data results on the return on starting prices and final prices show that the measure does not affect at all, as can be seen by the insignificant dummy variable coefficient δ (Annex 2).

Figure 2.



Estimation of the hedonic model, with and without control by propensity score, show that negative CAAR after the date of adoption. We tested several estimation windows with 3 different cut-off dates: 180 days before the adoption of mortgage amortization rule (2016-01-02), date of announcement of the decision by FI (2016-04-20) and 30 days before the adoption of mortgage amortization rule.

start of train period	end of train period /start of test period	end of test period
2015-03-02	2016-01-02	2017-06-25
2015-03-02	2016-04-19	2017-06-25
2015-03-02	2016-06-01	2017-06-25

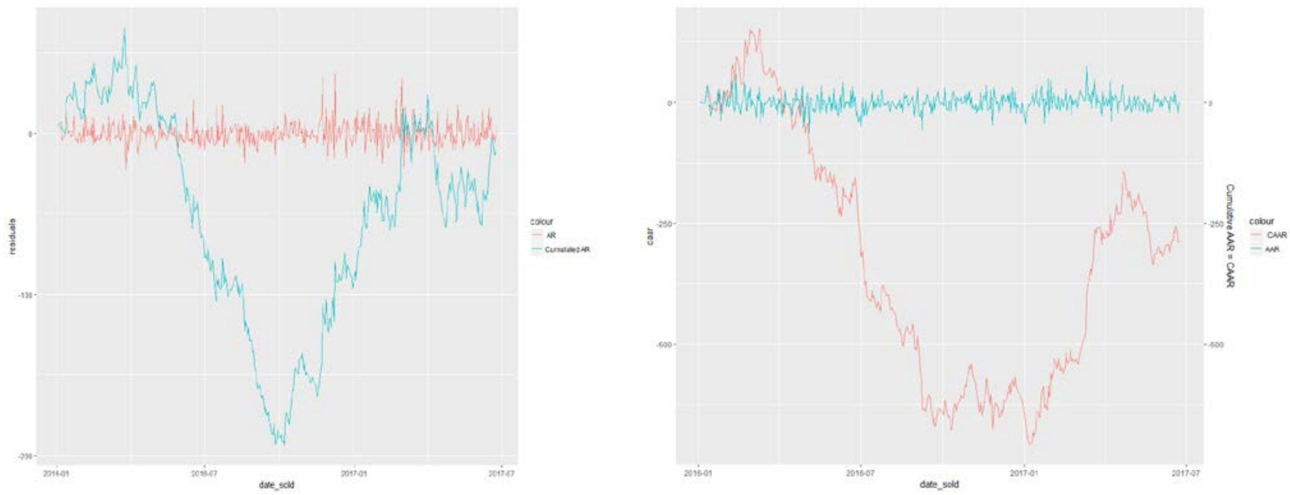
We have estimated hedonic models using 3 variables: bidding premium (Annex 3), staring price per m2 (annex 4) and final price per m2 (Annex 5).

Calculated CAARs from the hedonic models show negative CAARs (Figure 3) for all 3 variables. It should be noted that in some models in the far end of the data, the CAARs not just reversed back, but they even enter the positive territory. It possibly could mean that there was some new positive surprise or that model fundamentals have changed, so we have to take into consider only the shorter end of the CAARs.

Estimated coefficients for the premium are significant except for "the floor" of the apartment. Premiums are higher for larger and older apartments, but smaller for apartments with more rooms. In the model for the premiums we have included starting price as the independent variable, which showed positive coefficient. Adjusted R square for fitted premium are around 20% and lower then for the fitted prices per m2 (around 81%).

Estimated coefficients for the prices are all significant. Prices are higher for the apartment on higher floors and with more rooms. Price per m2 falls for larger and older apartments.

Figure 3. CAARs using hedonic model (start test period, a = premium, b = price per m2)

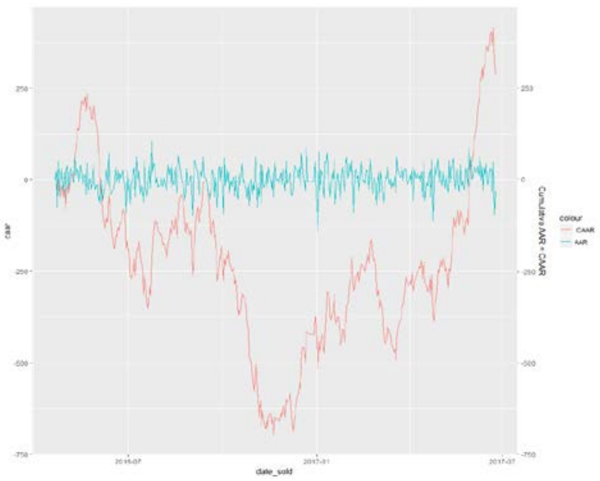


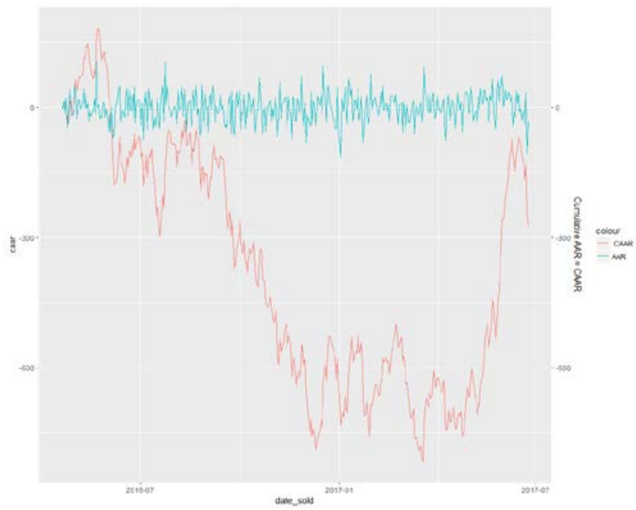
We have estimated spatial models using 2 variables: staring price per m2 (Annex 6) and final price per m2 (Annex 7).

Calculated CAARs from the spatial models show negative CAARs (Figure 4) for the 2 variables.

Estimated coefficients for the CAARs on prices are significant, except for the year of building of the apartment. With the increase of the apartment size, price per m2 decrease. As the floor of the apartment is increasing, the price per m2 is also increasing. Coefficient of the spatial autocorrelation is significant and positive, with values around 0.81. Residual correlation is small ranging between 0.02 and 0.06. AIC for the spatial model is far smaller than for the linear model.

Figure 4. CAARs using spatial model (start test period, a = premium, b = price per m2)





Conclusion

Our results showed that there was effect of the mandatory amortization rule as macroprudential measure on the bidding premium and housing prices (starting and final auction prices). We found negative CAARs after the day of the adoption of the measure. To the extent that house prices reflect rational expectations of future changes in fundamentals, this negative price response could imply negative prospects in the underlying housing market as perceived by market agents.

When we compare the results from parametric and semi-parametric (propensity score) event analyses, we find that the semi-parametric analysis generates moderately larger estimated effects of the new rule on housing prices. Negative CAARs were confirmed by both hedonic and spatial models. Far lower AIC statistics prove that spatial models are better modeling the price/premium dynamics and can compensate for the omitted variables.

Panel data results on the price dynamics were not very significant. Only premium changes showed statistical significance, but they were mixed as they initially show stagnation in the dynamics of the premium, but then display positive jump, opposite to the expected effects from the measure. Other coefficients from the panel data were not significant, so probably this analysis should be further enhanced with more variables, which might change the perceived dynamics.

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Appendix 1 – Timeline of adopted macroprudential measures

Macroprudential Measures Adopted since 2011

Measure	Implementation
Maximum LTV ratio, 85 percent	October 2010
Risk-weight floor for mortgages, 15 percent	May 2013
LCR regulation, including in euro, U.S. dollar, and total	January 2014
Pillar II capital add-on 2 percent for the four largest banks	September 2014
Risk-weight floor for mortgages, 25 percent	September 2014
Systemic risk buffer 3 percent for four largest banks	January 2015
Counter-cyclical capital buffer activated at 1 percent	September 2015
Amortization requirement	June 2016
Counter-cyclical capital buffer raised to 1.5 percent	June 2016
Counter-cyclical capital buffer raised to 2.0 percent	March 2017

Appendix 2a - Panel data tests

variable	type	Testing for random effects: Breusch-Pagan Lagrange multiplier (LM)	F Test	F Test	Hausman test	Pesaran CD test for cross-sectional dependence	Breusch-Pagan LM test for cross-sectional dependence
		OLS vs random	fixed vs pooled	fixed time vs fixed	random vs fixed		
premium	median	random	fixed	fixed time	random	0,000	0,023
start price per m2	median	OLS	pooled	fixed	fixed	0,448	0,020
final price per m2	median	OLS	pooled	fixed time	random	0,065	0,070

Appendix 2b - Panel data results

Median

Premium

model	OLS			pooled			fixed			random		
(Intercept)	-0,011	0,797		-0,011	0,797					-0,043	0,336	
floor	-0,008	0,188		-0,008	0,188		0,002	0,720		0,001	0,922	
year of building	0,000	0,184		0,000	0,184		0,001	0,188		0,001	0,191	
rooms	-0,010	0,540		-0,010	0,540		-0,004	0,794		-0,004	0,759	
size	0,001	0,105		0,001	0,105		0,001	0,078	.	0,001	0,080	.
dummy	0,047	0,000	***	0,047	0,000	***	0,047	0,000	***	0,047	0,000	***
Adjusted R-squared:	0,098			0,098			0,095			0,117		
theta:										0,638		

Returns on start price per m2

model	OLS			pooled			fixed			random		
(Intercept)	3,046	0,029	*	3,046	0,029	*				2,766	0,038	*
floor	0,160	0,436		0,160	0,436		0,100	0,680		0,164	0,383	
year of building	-0,034	0,004	**	-0,034	0,004	**	-0,046	0,002	**	-0,030	0,006	**
rooms	-0,593	0,515		-0,593	0,515		-0,698	0,453		-0,549	0,545	
size	-0,001	0,984		-0,001	0,984		0,001	0,975		-0,002	0,967	
dummy	-0,020	0,940		-0,020	0,940		-0,038	0,884		-0,013	0,959	
Adjusted R-squared:	0,024			0,024			0,005			0,021		
theta:										-0,341		

Returns on final price per m2

model	OLS			pooled			fixed			random		
(Intercept)	1,900	0,166		1,900	0,166					1,646	0,208	
floor	0,169	0,384		0,169	0,384		0,142	0,539		0,156	0,374	
year of building	-0,029	0,011	*	-0,029	0,011	*	-0,042	0,003	**	-0,024	0,021	*
rooms	-1,070	0,228		-1,070	0,228		-1,155	0,201		-1,036	0,241	
size	0,029	0,428		0,029	0,428		0,031	0,402		0,028	0,443	
dummy	0,033	0,896		0,033	0,896		0,012	0,964		0,042	0,871	
Adjusted R-squared:	0,021			0,021			0,004			0,017		
theta:										-0,386		

Appendix 3 - Hedonic model on bidding premium

premium	30 day before event date			72 days before event date			180 days before the event date		
	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period
	2015-03-02	2016-06-01	2017-06-25	2015-03-02	2016-04-19	2017-06-25	2015-03-02	2016-01-02	2017-06-25
	Estimate	Pr(>|t|)		Estimate	Pr(>|t|)		Estimate	Pr(>|t|)	
(Intercept)	3,4695	0,0000	***	3,4944	0,0000	***	3,5212	0,0000	***
log(price_per_m2)	0,1259	0,0000	***	0,1214	0,0000	***	0,1256	0,0000	***
time_dummy	0,0000	0,0051	***	0,0000	0,0063	***	0,0000	0,0213	***
floor	-0,0012	0,3083		-0,0013	0,2435		-0,0022	0,0720	
year of bulding	0,0004	0,0001	***	0,0004	0,0002	***	0,0004	0,0022	***
rooms	-0,0128	0,0081	***	-0,0170	0,0004	***	-0,0191	0,0002	***
size	0,0008	0,0002	***	0,0009	0,0000	***	0,0010	0,0000	***
Adjusted R-squared:	0,2222			0,2184			0,2094		
	Control	Treated		Control	Treated		Control	Treated	
All	3839	3482		3443	3878		2584	4737	
Matched	2515	2515		2563	2563		2286	2286	

Appendix 4 - Hedonic model on start price per m2

start price per m2	30 day before adoption date			72 days before adoption date			180 days before the adoption date		
	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period
	2015-03-02	2016-06-01	2017-06-25	2015-03-02	2016-04-19	2017-06-25	2015-03-02	2016-01-02	2017-06-25
	Estimate	Pr(>|t|)		Estimate	Pr(>|t|)		Estimate	Pr(>|t|)	
(Intercept)	10,1825	0,0000	***	10,1947	0,0000	***	9,6147	0,0000	***
time_dummy	0,0004	0,0000	***	0,0003	0,0000	***	0,0004	0,0000	***
floor	0,0138	0,0000	***	0,0145	0,0000	***	0,0125	0,0000	***
year of building	-0,0005	0,0359	*	-0,0004	0,0712	.	-0,0004	0,1018	
rooms	0,0352	0,0004	***	0,0538	0,0000	***	0,0510	0,0000	***
size	-0,0041	0,0000	***	-0,0051	0,0000	***	-0,0049	0,0000	***
….									
Adjusted R-squared:	0,8246			0,8349			0,8376		
	Control	Treated		Control	Treated		Control	Treated	
All	3839	3482		3422	3899		2583	4738	
Matched	3054	3054		3118	3118		2453	2453	

Appendix 5 - Hedonic model on final price per m2

price per m2	30 day before adoption date			72 days before adoption date			180 days before the adoption date		
	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period
	2015-03-02	2016-06-01	2017-06-25	2015-03-02	2016-04-19	2017-06-25	2015-03-02	2016-01-02	2017-06-25
	Estimate	Pr(>|t|)		Estimate	Pr(>|t|)		Estimate	Pr(>|t|)	
(Intercept)	10,3505	0,0000	***	10,2579	0,0000	***	9,7656	0,0000	***
time_dummy	0,0004	0,0000	***	0,0004	0,0000	***	0,0004	0,0000	***
floor	0,0148	0,0000	***	0,0165	0,0000	***	0,0123	0,0000	***
year of building	-0,0001	0,5473	*	-0,0001	0,6693	,	-0,0002	0,4758	
rooms	0,0363	0,0005	***	0,0400	0,0001	***	0,0412	0,0002	***
size	-0,0044	0,0000	***	-0,0046	0,0000	***	-0,0046	0,0000	***
….									
Adjusted R-squared:	0,8105			0,8246			0,8276		
	Control	Treated		Control	Treated		Control	Treated	
All	3842	3479		3424	3897		2585	4736	
Matched	3057	3057		3117	3117		2456	2456	

Appendix 6 - Spatial autoregressive model on start price per m2

start price per m2	30 day before adoption date			72 days before adoption date			180 days before the adoption date		
	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period
	2015-03-02	2016-06-01	2017-06-25	2015-03-02	2016-04-19	2017-06-25	2015-03-02	2016-01-02	2017-06-25
	Estimate	Pr(>|t|)		Estimate	Pr(>|t|)		Estimate	Pr(>|t|)	
(Intercept)	1,9624	0,0000	***	1,9375	0,0000	***	1,9635	0,0000	***
time_dummy	0,0003	0,0000	***	0,0003	0,0000	***	0,0003	0,0000	***
floor	0,0105	0,0000	***	0,0122	0,0000	***	0,0093	0,0002	***
year of building	0,0002	0,2716		0,0001	0,3540		0,0000	0,8769	
size	-0,0022	0,0000	***	-0,0022	0,0000	***	-0,0022	0,0000	***
rho	0,8287	0,0000	***	0,8314	0,0000	***	0,8312	0,0000	***
residual autocorrelation	0,0296	0,0060	***	0,0343	0,0040	***	0,0563	0,0010	***
AIC for spatial model	69,7			68,8			241,2		
AIC for linear model	4040,3			4231,3			3382,5		
Number of observations:	3054			3118			2453		

Appendix 7 - Spatial autoregressive model on final price per m2

price per m2	30 day before adoption date			72 days before adoption date			180 days before the adoption date		
	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period	start of train period	end of train period /start of test period	end of test period
	2015-03-02	2016-06-01	2017-06-25	2015-03-02	2016-04-19	2017-06-25	2015-03-02	2016-01-02	2017-06-25
	Estimate	Pr(>|t|)		Estimate	Pr(>|t|)		Estimate	Pr(>|t|)	
(Intercept)	2,0727	0,0000	***	2,0912	0,0000	***	2,1541	0,0000	***
time_dummy	0,0004	0,0000	***	0,0004	0,0000	***	0,0004	0,0000	***
floor	0,0123	0,0000	***	0,0118	0,0000	***	0,0092	0,0003	***
year of building	0,0003	0,1335		0,0003	0,0965	.	0,0003	0,1363	
size	-0,0024	0,0000	***	-0,0023	0,0000	***	-0,0024	0,0000	***
rho	0,8236	0,0000	***	0,8219	0,0000	***	0,8169	0,0000	***
residual autocorrelation	0,0445	0,0010	***	0,0471	0,0010	***	0,0648	0,0010	***
AIC for spatial model	176,3			184,4			377,5		
AIC for linear model	4050,4			4172,3			2456,0		
Number of observations:	3057			3117			2456		